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Insight from a Wholesaler of Franchise Retail Stores

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BY
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NOTE ON THE AUTHOR

Flemming Max Møller Christensen

Flemming was born in 1987 in Horsens, Denmark. In 2007 he started an apprenticeship in warehouse and logistics operations at Fredericia-Middelfart Technical College in Fredericia. After completion in 2010, he enrolled in a professional bachelor' degree in value chain management at VIA University College in Horsens, from which he graduated with honours in 2014. Following this, he continued his education with a master's degree in operations and supply chain management from Aalborg University, Aalborg, from which he graduated in 2016.

Since February 2017, Flemming has been an industrial PhD fellow at Aalborg University's Department of Materials and Production as part of the Centre for Logistics (CELOG) research group. During his PhD study, he has had several periods as visiting researcher at the Division of Supply and Operations Management at Chalmers University, Gothenburg Sweden.

Professionally, Flemming has worked within grocery retailing for more than a decade; first as operations employee (full-time) from 2005–2010, then as logistics assistant from 2010–2016 (part-time), with an additional one year part-time employment at a large food manufacturer from 2012–2013. Since 2016, he worked as supply chain engineer at one of Denmark' largest grocery wholesalers, until he started his industrial PhD study in February 2017, together with the wholesaler and in collaboration with Aalborg University, co-funded by the Innovation Fund Denmark. Additionally, during his PhD study, Flemming has worked as teaching assistant since 2018, where he has held classes in logistics, transportation, production forecasting and warehouse management and design, at bachelor and masters level.

His research interest is within collaborative materials management of perishable products, (real-time) information sharing and differentiated planning and control in fresh food supply chains. In 2019, he received the John Burbidge Award for Best Paper for the conference proceeding “Asymmetrical Evaluation of Forecasting Models through Fresh Food Product Characteristics“ together with his co-authors at the annual APMS-conference in Austin Texas, USA.

ENGLISH SUMMARY

Today's competitive grocery retailing is experiencing an increasing demand for fresh food products (Nielsen, 2018, 2017) with ever-growing consumer requirements for the availability of fresh products at a low price (Jacobsen and Bjerre, 2015). Product availability refers to the availability of a desired product in acceptable condition on the shelf in the retail store and ready for purchase when the consumer wants it (Ettouzani et al., 2012). If not available, consumers may either not purchase the product, postpone the purchase until later, substitute the product with another (within or from another brand) or even switch store (Aastrup and Kotzab, 2010; Hübner, 2011). This results in a lost sale, thus profit loss, and causes unnecessary noise in any further demand planning.

Certainly, building inventories appears to be a rather straightforward approach to meet the fluctuating demand and ensure product availability. However, fresh food products are perishable with a short shelf life. They may turn harmful for human consumption even a few days after being processed. Thus, having too high inventory levels not only reduces the freshness of the products, it also entails food waste along the supply chain.

Food waste is on climate agendas around the world. It has a double climatic impact, influencing the environment both during production and through treatment as waste (Stenmarck et al., 2011). In Denmark alone, more than 3,000 shopping carts filled with grocery products end as waste every day (Stenmarck et al., 2016). In fact, studies report that around one-quarter of processed food and upwards of one-third of the harvested raw material end up as food waste (Kummu et al., 2012; Mena et al., 2014; Parfitt et al., 2010), amounting to hundreds of billions of EUR in economic, environmental and social costs (Fattibene and Bianchi, 2017).

One reason for the food waste, i.e. over-supply, and product unavailability in stores, i.e. under-supply, is poor replenishment planning and control, i.e. information sharing, demand forecasting and inventory control (Gruen et al., 2002; Kummu et al., 2012; Mena et al., 2014, 2011). This PhD study examines

how fresh food supply chains can align the demand and supply through improved replenishment planning and control. The study reflects two propositions in fresh food literature: “the shorter the shelf life of the product (the more perishable), the stronger the positive relationship between information sharing and supply chain performance” (Lusiantoro et al., 2018, p. 276) and “improved supply chain wide transparency of demand information upstream in the supply network (…) can reduce supply-chain wide food waste” (Mena et al., 2014, p. 152).

In addition, fresh food products differ significantly from one another in their so-called planning environment characteristics relating to the product, demand, supply and production. Examples of these include e.g. differences in time to produce and process, different raw material availability for different products and/or throughout the year as well as specialised and complex processing requirements (i.e. different processing) (Entrup, 2005; Romsdal, 2014). Thus, any ‘one-for-all’ approach to align demand and supply is expected to lead to increased risk of food waste. Following the doctrine “share only information that improves supply chain performance” (Kaipia and Hartiala, 2006, p. 385), this study thus unfolds from the hypothesis that reflecting the planning environment characteristics in replenishment planning and control leads to higher availability and freshness with low waste and inventory.

A main part of replenishment planning and control is information sharing, which supports decision-making and is considered a pivotal remedy to reduce under/oversupply (e.g. Lusiantoro et al., 2018) and the bullwhip effect (Disney and Towill, 2003a). Effective information sharing is sharing the *right* information, with the *right* parties, at the *right* place *and* time, in the *right* way and under the *right* circumstances (Huang, Lau, and Mak 2003; Kembro and Näslund 2014).

Studies suggest that information sharing be based on an “understanding of all the supply chain attributes rather than relying on generalizations” (Nakandala et al., 2017, p. 114). One supply chain stage which seems to have an understanding of the divergent and convergent flows of information and products in the supply chain is the wholesaler or distribution centres, since they link supply and demand (Alftan et al., 2015; Hübner et al., 2013).

To adequately understand the planning environment characteristics and how they affect the effective replenishment planning and control, two main research questions are put forth.

> **Question 1**: How do planning environment characteristics impact information sharing during replenishment planning and control in fresh food retailing?

Question 1a: What are the planning environment characteristics in fresh food retailing, and how are they characterised?

Question 1b: How is information sharing during replenishment planning and control in fresh food retailing characterised?

Question 2: How can wholesaler effectively plan and control replenishments according to the fresh food planning environment characteristics, and what is the impact on performance?

For RQ1, two literature studies were carried out. The first identified the planning environment characteristics reported in the literature to create a framework for the further empirical investigation. The second identified and synthesised the facets of shared information reported in the literature in order to create a taxonomy for empirical investigation. Afterwards, several case studies were undertaken to understand the characterisation of planning environment characteristics and information sharing in fresh food retailing and how planning environment characteristics impact the information sharing. The case studies involved one of Denmark's largest grocery wholesalers, the fastest growing retail chain in Denmark and five fresh food processors.

For RQ2, different literature studies founded the solution proposal for ensuring effective replenishment planning and control, i.e. differentiating the information sharing and order decision-making according to the planning environment characteristics. The studies departed within forecasting evaluation, inventory control and real-time information sharing. Two case studies were undertaken in order to test the potential improvement of the suggested solutions. One single case study including 17 fresh food products at a wholesaler was undertaken to examine the impact of differentiated forecasting evaluation (according to shelf life) on freshness, fill-rate and waste, by comparing to conventionally used evaluation measures. One multi-case study including 50 fresh food products at five fresh food processors, one wholesaler and a 329 retail stores was undertaken to examine the impact of differentiated real-time POS based information sharing (according to processing method and demand type) on freshness, fill-rate and waste level, by comparing to historical order-based information sharing.

The main contributions of this thesis are summarised as follow:

Regarding information sharing:

- Identification and synthesis of six information sharing facets, which combined provide a taxonomy for investigating and mapping the effective information sharing in supply chains.
- Development of 19 propositions for effective information sharing, considering the effect of planning environment characteristics evident at FFP processors.
- An empirical study of real-time point-of-sales-based information sharing during demand forecasting and inventory control across 50 FFPs, with further comparison against order-based information sharing and consideration of product classification according to processing methods.
    - Computations show that real-time POS-based information sharing generally outperforms order-based information sharing and that mixed information sharing at product level leads to the most significant improvement in performance.
    - Further, the performance differs across demand type and processing method and an increase in performance is generally seen by a marginal reduction in fill-rate, while significant reduction in waste levels and increase in freshness is observed.

Regarding planning environment characteristics:

- Identification of 29 planning environment characteristics and their impact on materials requirement planning (12), master production scheduling (15) or both (2), at four different types of FFP processors.
- Identification of 12 new planning environment characteristics: ageing, dairy prices, import from non-EU to EU, product upgradeability, stability in meat classification, time of year for meat-type, time of year for meat conformity, weather dependent supply, organic, slaughtering hierarchy and time of year for holidays.

Regarding order decision-making:

- Development of a multi-product inventory heuristic EWA_{3SL} that differentiates according to supplier fill-rate, price reduction, demand substitution and inventory substitution.

- Development of a four-dimensional model for differentiated RP&C, that reflects product perishability, coefficient of variation in demand, supply lead-time and (customer) order frequency.

- Development of a new asymmetrical forecasting accuracy measure wSLE that considers product shelf life and its relation to the following days' demand.

- An empirical evaluation of differentiated demand forecast evaluation across 17 FFPs considering fill-rate and waste, with a comparison to three commonly used accuracy measures in retailing.

    - wSLE ensures higher levels of freshness and lower levels of waste when comparing to other accuracy measures.
    - Findings show that including the shelf life and the differentiated impact of over-forecasting with/without price reduction gives marginally lower service levels but an improved freshness of fresh food products and a lower inventory level.

DANSK RESUME

Dagens dagligvarehandel er konkurrencefyldt med en stigende efterspørgsel efter friske fødevarer (Nielsen, 2018, 2017) og stadigt voksende forbrugerkrav om tilgængelighed af friske produkter til en lav pris (Jacobsen and Bjerre, 2015). Produkt tilgængelighed henviser til tilgængeligheden af et ønsket produkt i en acceptabel stand på hylden i butikken og klar til køb, når forbrugeren ønsker det (Ettouzani et al., 2012). Hvis produktet ikke er tilgængeligt, kan forbrugerne vælge at enten ikke købe produktet, udsætte købet til senere, erstatte produktet med et andet (indenfor samme eller til et andet mærke) eller endda skifte butik (Aastrup and Kotzab, 2010; Hübner, 2011). Resultatet af dette er tabt salg og dermed tabt profit samt forårsager unødvendig støj i yderligere planlægning.

Opbygning af lagre er en åbenlys måde at imødekomme svingende efterspørgsel på og derved sikre produkt tilgængelighed. Friske fødevarer er dog letfordærvelige og har en kort holdbarhed. De kan endda blive sundhedsfarlige selv få dage efter produktion. Derfor vil for høje lagerniveauer ikke kun mindske friskheden af produkterne, men også medføre madspild langs forsyningskæden.

Madspild er på klimadagsordener over hele verden. Det har en dobbelt klimapåvirkning idet at det påvirker miljøet både under produktionen og efterfølgende gennem behandlingen som affald (Stenmarck et al., 2011). Alene i Danmark ender mere end 3.000 indkøbsvogne fyldt med dagligvareprodukter som affald hver dag (Stenmarck et al., 2016). Undersøgelser viser, at omkring en fjerdedel af den forarbejdede mad, og op mod en tredjedel af det høstede råmateriale, ender som madspild (Kummu et al., 2012; Mena et al., 2014; Parfitt et al., 2010), som koster hundreder af milliarder EUR i økonomiske, miljømæssige og sociale omkostninger (Fattibene and Bianchi, 2017).

En af årsagerne til madspildet, dvs. overtilgængelighed, og produktets utilgængelighed i butikker, dvs. underforsyning, er dårlig planlægning og styring af genopfyldninger, herunder informationsdeling, forecasting og lagerstyring (Gruen et al., 2002; Kummu et al., 2012; Mena et al., 2014, 2011). Dette ph.d.-studie undersøger, hvordan forsyningskæder med friske fødevarer kan tilpasse efterspørgsel og udbud igennem en forbedret planlægning og styring af

genopfyldninger. Studiet afspejler to propositioner fra litteraturen: "Jo kortere holdbarhed produktet har (jo mere letfordærveligt), des stærkere er det positive forhold mellem informationsdeling og forsyningskædens ydeevne" [frit oversat] (Lusiantoro et al., 2018, p. 276) og "forbedret gennemsigtighed af efterspørgselsinformation i forsyningskæden (...) kan reducere madspildet i kæden" [frit oversat] (Mena et al., 2014, p. 152).

Derudover adskiller friske fødevarer sig også markant fra hinanden i deres såkaldte planlægningskarakteristika vedrørende produkt, efterspørgsel, udbud og produktion. Eksempler på disse er f.eks. forskelle i produktionstid og forarbejdning, forskellig tilgængelighed af råvarer for forskellige produkter og/eller i løbet af året, specialiseret og kompleks forarbejdning (Entrup, 2005; Romsdal, 2014). Enhver "en-for-alle"-tilgang til at tilpasse efterspørgsel og udbud forventes således at føre til øget risiko for madspild. I overensstemmelse med doktrinen "del kun information, der forbedrer forsyningskædens ydeevne" [frit oversat] (Kaipia and Hartiala, 2006, p. 385), udspringer dette studie således fra hypotesen, at afspejling af planlægningskarakteristikaene i planlægningen af styring af genopfyldninger fører til højere tilgængelighed og friskhed samt lavere spild og lagerbeholdning.

En stor del af planlægning og styring af genopfyldning omhandler deling af informationer, da det understøtter beslutningstagning og betragtes som et afgørende middel til at reducere under-/overforsyning (f.eks. Lusiantoro et al., 2018) og bullwhip-effekt (Disney and Towill, 2003a). Effektiv informations-deling handler om at dele de rigtige oplysninger med de rigtige parter på det rette sted og tidspunkt, på den rigtige måde og under de rette omstændigheder (Huang, Lau, and Mak 2003; Kembro and Näslund 2014).

Studier foreslår at basere informationsdelingen på en "forståelse af alle forsyningskædeattributter snarere end at stole på generaliseringer" [frit oversat] (Nakandala et al., 2017, p. 114). En aktør i forsyningskæden som synes at have en forståelse for de divergerende og konvergerende strømme af information og produkter, er grossisten eller distributionscentre, eftersom de forbinder udbud fra industrien og efterspørgsel fra kunderne (Alftan et al., 2015; Hübner et al., 2013).

For at opnå tilstrækkelig forståelighed for planlægningskarakteristikaene og deres indvirkning på den effektive planlægning og styring af genopfyldninger, fremsættes to forskningsspørgsmål.

> **Spørgsmål 1**: Hvordan indvirker planlægningskarakteristika informationsdelingen i løbet af planlægningen og styringen af genopfyldninger i detailhandel med friske fødevarer?

Spørgsmål 1a: Hvad er planlægningskarakteristikaene i detailhandel med friske fødevarer, og hvordan karakteriseres de?

Spørgsmål 1b: Hvordan karakteriseres informationsdeling under genopfyldningsplanlægning og -kontrol i detailhandel med friske fødevarer?

Spørgsmål 2: Hvordan kan grossisten effektivt planlægge og styre genopfyldninger ifølge planlægningskarakteristikaene for friske fødevarer, og hvad er indvirkningen på performance?

For forskningsspørgsmål 1 blev der udført to litteraturstudier. Det første identificerede de planlægningskarakteristika som er i litteraturen, for at skabe en ramme for den videre empiriske undersøgelse. Det andet identificerede og syntetiserede de facetter af informationsdeling som rapporteret i litteraturen for at skabe en taksonomi for den empiriske efterforskning. Derefter blev flere casestudier udført for at forstå hvordan planlægningskarakteristika og informationsdeling karakteriseres i detailhandel med friske fødevarer. Endvidere, hvordan planlægningskarakteristika påvirker informationsdelingen. Casestudierne involverede en af Danmarks største dagligvaregrossister, den hurtigst voksende detailkæde i Danmark samt fem producenter af friske fødevarer.

For forskningsspørgsmål 2 udgjorde forskellige litteraturstudier grundlaget for løsningsforslaget til sikring af effektiv planlægning og styring af genopfyldninger, dvs. differentiering af informations deling og disponering ifølge planlægningskarakteristikaene. Studierne fokuserede på evaluering af forecasts, lagerstyring og informationsdeling i realtid. To casestudier testede den potentielle forbedring af de foreslåede løsninger. Det ene enkelt-casestudie omhandlede 17 produkter hos grossisten og undersøgte indvirkningen af differentieret evaluering af forecast (ifølge holdbarhed) på friskhed, fyldningsgrad og madspild, ved at sammenligne mod konventionelle metoder for evaluering. Det andet multi-casestudie omhandlede 50 produkter hos fem producenter, en grossist og 329 detailbutikker og undersøgte indvirkningen af differentieret POS-baseret informationsdeling i realtid (ifølge forarbejdnings-metode og type af efterspørgsel) på friskhed, fyldningsgrad og madspild ved at sammenligne mod historisk ordrebaseret informationsdeling.

Hovedbidragene af dette ph.d.-studie kan opsummeres som følger:

Vedrørende informationsdeling:

- Identificering og syntese af seks facetter for informationsdeling, som tilsammen udgør en taksonomi til undersøgelse og kortlægning af effektiv informationsdeling i forsyningskæder.
- Nitten forslag til at sikre effektiv informationsdeling under hensyntagen til planlægningskarakteristikaenes effekt hos producenten.
- Empirisk undersøgelse af realtids- og POS-baseret informationsdeling under forecasting og lagerstyring på tværs af 50 produkter, med yderligere sammenligning mod ordrebaseret informationsdeling og klassificering ifølge forarbejdningsmetode.
    - Beregninger viser, at realtids POS-baseret informationsdeling generelt performer bedre end ordrebaseret informationsdeling, og at blandet informationsdeling på produktniveau fører til den mest betydningsfulde forbedring i performance.
    - Derudover adskiller performance sig på tværs af efterspørgselstype og produktions-/forarbejdningsmetode, og en forbedret performance ses generelt på bekostning af en marginal reduktion i fyldningsgrad, mens der ses en betydelig reduktion i spild og forøget friskhed.

Vedrørende planlægningskarakteristika:

- Identificering af 29 planlægningskarakteristika og deres indvirkning på materialebehovsplanlægning (12), masterproduktionsplanlægning (15) eller begge dele (2) på fire forskellige typer af producenter.
- Identificering af 12 nye planlægningskarakteristika: modning, mejeripriser, import fra ikke-EU til EU, produktopgradering, stabilitet i kødklassificering, årstid for kødtype, årstid for kødoverensstemmelse, vejrafhængig forsyning, organisk, slagtningshierarki og årstid for helligdage.

Vedrørende lagerstyring:

- Udvikling af en heuristisk EWA_{3SL} for flere produkter, som differentierer i forhold til leverandørens leveringsevne, prisreduktion, efterspørgsels erstatning og varesubstitution.

- Udvikling af en fire-dimensional model for differentieret planlægning og styring af genopfyldninger, som afspejler produktets fordærvelighed, koefficient for variation i efterspørgsel, leveringstid og (kunde) ordrefrekvens.

- Udvikling af en ny differentieret evalueringsmetode for forecast wSLE, som tager hensyn til produktets holdbarhed og dets forhold til efterfølgende dages efterspørgsel.

- Empirisk studie af differentieret forecast evaluering på tværs af 17 produkter med fokus på fyldningsgrad og madspild, sammenlignet med tre almindeligt anvendte evalueringsmetoder i detailhandel.

    - wSLE sikrer højere friskhed og lavere spild sammenlignet med de andre evalueringsmetoder.
    - Resultaterne viser, at inkludering af holdbarhed og den differentierede virkning af over-forecasting med/uden prisnedsættelse giver marginalt lavere serviceniveau, men en forbedret friskhed af friske fødevarer og et lavere lagerniveau.

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This thesis is the result of an Industrial PhD study conducted with one of the biggest actors in Danish grocery retailing, from 2017 to 2020. In this manner, the thesis has a two-fold aim of advancing and contributing both to the practices and understanding within the industrial partner as well as current knowledge in the field of demand and supply chain planning. In some ways this thesis represents the culmination of a journey which started more than a decade ago, when I first entered the grocery retailing industry. It is a journey which has not ended yet, but merely shifted to a new level in the ongoing learning process. Hence, in other ways, this thesis is a symbol of a true journey which is merely about to begin.

This research could not have been carried out without the support of several people. I consider myself fortunate to have had the opportunity to get to know these people and learn from their immense knowledge and experience, and I owe a big thank you to each single person.

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Aalborg, October 2020

Flemming Max Møller Christensen

TABLE OF CONTENT

ABBREVIATIONS

ARP	Automatic replenishment program
CASB	Combined age-and-stock-based policy
CBMF	Collaborative buyer-managed forecasting
CPFR	Collaborative planning, forecasting and replenishment
CR(P)	Continuous replenishment (program)
ECR	Efficient consumer response
EDI	Electronic data interchange
ERP	Enterprise resource system
EWA	Not an abbreviation, but the name of an inventory policy
FFP	Fresh food product
(w)MAPE	(weighted) Mean absolute percentage error
(w)ME	(weighted) Mean error
MRP	Material requirements planning
MPS	Master production schedule
OIR	Old inventory ratio policy
OOS	Out-of-stock
PCSO	Process of collaborative store ordering
PEC	Planning environment characteristic
POS	Point-of-sales
RP&C	Replenishment planning and control
RQ	Research question
TR	Traditional replenishment
(w)RMSE	(weighted) Root mean square error
VMI	Vendor managed inventory
VOI	Vendor owned inventory
wSLE	weighted shelf life error
wQL	weighted quantile loss

LIST OF PAPERS

Paper #1
Christensen, Flemming M. M., Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2017b. "**Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime**." In *Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing – Proceedings*, *Part II*, pp. 139–147.

Paper #2
Christensen, Flemming M. M., Jonsson, Patrik, Dukovska-Popovska, Iskra, and Steger-Jensen, Kenn. 2019. "**Information Sharing for Replenishment Planning and Control in Fresh Food Supply Chains: A Planning Environment Perspective**." To be submitted to *Production Planning & Control* for third review, October 2020.

Paper #3
Christensen, Flemming M. M., Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2017a. "**Replenishment Planning of Fresh Meat Products: Case Study from a Danish Wholesaler**." In *Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing – Proceedings*, *Part II*, pp. 130–138.

Paper #4
Mantravadi, Soujanya, Møller, Charles and Christensen, Flemming M. M. 2018. "**Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration**." In *International Conference on Smart Systems and Technologies (SST): IEEE Region 8*, Croatian Academy of Engineering, pp. 133–137.

Paper #5
Christensen, Flemming M. M., Mantravadi, Soujanya, Dukovska-Popovska, Iskra, Hvolby, Hans-Henrik, Steger-Jensen, Kenn and Møller, Charles. 2019. "**Horizontal Integration in Fresh Food Supply Chain**." In *Advances in Production Management Systems, Production Management for the Factory of the Future – Proceedings, Part II*, pp. 164–172.

Paper #6
Christensen, Flemming M. M., Bojer, Casper S., Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2019. "**Developing New Forecasting Accuracy Measure Considering Product's Shelf Life: Effect on Availability and Waste**." Submitted to *Journal of Cleaner Production* for third review, September 2020.

Paper #7
Christensen, Flemming M. M., Steger-Jensen, Kenn and Dukovska-Popovska, Iskra. 2017. "**Product Characteristics for Differentiated Replenishment Planning of Meat Products**." In *International Symposium of Logistics*, ISL, pp. 594–601. Ljubljana.

Paper #8
Christensen, F. M. M., Steger-Jensen, K. and Dukovska-Popovska, I. 2020. "**Managing Perishable Multi-Product Inventory with Supplier Fill-Rate, Price Reduction and Substitution**." In *Advances in Production Management Systems, Towards Smart and Digital Manufacturing – Proceedings, Part II*, pp. 640–649.

Paper #9
Christensen, Flemming M. M., Meldgaard, Jens Peder, Jonsson, Patrik, Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2020. "**Real-Time Point-of-Sales Information Sharing in Fresh Food Supply Chain**." To be submitted to *International Journal of Production Economics* for first review, October 2020.

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INTRODUCTION

The grocery retailing industry has undergone significant changes during the past decades with e.g. online shopping with home delivery, self-checkouts in stores and pick-up points for already packed groceries. Today consumers require a broad assortment of high-quality products at a low price when shopping in retail stores. If a retail store does not manage to fulfil these requirements, consumers relentlessly postpone their purchase, purchase a different product or even purchase the product from a different store (Hübner, 2011). In fact, 60% of the grocery industry consider fresh products very important to their business (BlueYonder, 2017). In parallel with this, there is an ever-growing focus on reducing food waste. Since most grocery products are perishable and degrade over time, this places high requirements on the supply chains.

The aim of food supply chains in today's grocery retailing market is to satisfy consumers' requirements regarding product availability and freshness while keeping waste, inventory and cost levels at a minimum. Several collaborative programs have emerged since the 1990s to deal with the alignment of supply and demand in food supply chains. However, "only a few instances" of these programs are in use (Mena et al., 2014, p. 152), and they generally entail large consumption of resources in order to be implemented. Also, the programs are focused on a portion of suppliers and mainly directed for products with specific demand characterisation – without considering other planning characteristics such as product, supply, and processing specifics. Replenishment is one of the main processes in the programs that directly affects the product availability, freshness, inventory level and waste. However, the programs merely specify an overall frame for collaboration without looking into specifics of information sharing and order decision making while replenishing. This is challenging since food products are different from one another in terms of e.g. shelf life, time to produce and process and raw material availability. Thus, there is a need for in-depth understanding of how these product differences (expressed as planning environment characteristics) affect the replenishment planning and control.

This chapter presents the motivation for the topic of this research study by first clarifying the importance of fresh food retailing and fresh food product (FFP) characteristics. Thereafter follows a presentation of the challenges faced in fresh food retailing and the current approaches to solving these challenges. Next, the research objective and subsequent research questions are specified, along with the scope. The chapter ends with a thesis outline.

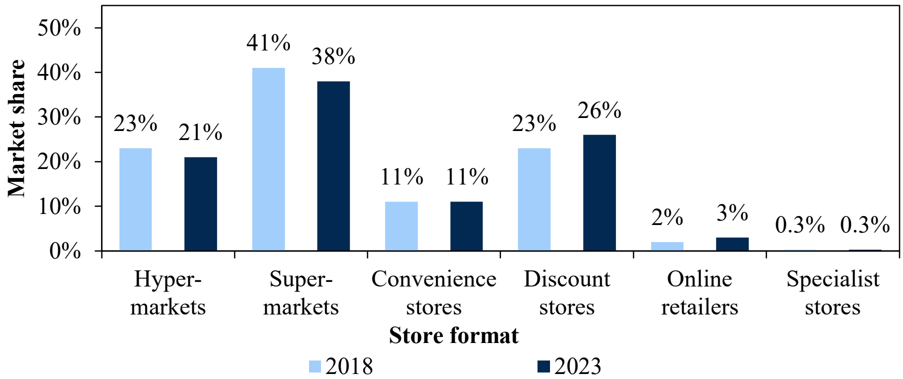
1.1. THE IMPORTANCE OF FRESH FOOD RETAILING

Grocery retailing relates to the activities up to the point when consumers buy the product, occurring within or between the wholesaler, distribution centre and/or retail store. Since the 2000s, the grocery retailing industry has experienced significant changes in how grocery products are conveyed and sold to consumers, as well as in demand for grocery products. Today's grocery retailing market is an enormous business with annual sales in Western Europe exceeding €540 billion – and worldwide yearly sales are expected to reach €11 trillion by 2021 (Distribution, 2016). In particular, fresh food products (FFPs) represent almost 25% of total sales and 45% of annual growth (Nielsen, 2018, 2017).

Consumers have ever higher requirements in terms of product assortment, price, availability and quality (freshness) (Kuhn and Sternbeck, 2013), and are increasingly aware of food waste and its environmental and social consequences. Further, consumers have (very) low involvement when grocery shopping. When an out-of-stock situation occurs or requirements for a given product are not met (due to e.g. reduced shelf life), consumers tend to either not purchase the product, postpone the purchase until later, substitute the product (within or from another brand) or even switch store (Aastrup and Kotzab, 2010; Hübner, 2011). This results first and foremost in a lost sale for the given products, subsequently causing additional variation in the demand, thus causing unnecessary noise and more difficulties in ensuring fresh products.

Today most grocery products are sold through six different store formats, each represented by different retail chains and hundreds or thousands of stores. Large corporations typically own one or several of these retail chains and supply the stores through corporate-owned warehouses and distribution centres. The market competition is fierce. Figure 1-1 illustrates the market share of the six store formats within European grocery retailing. Despite increasing online retailing, physical store formats expect to handle more than 96% of grocery shopping in the future. However, hypermarkets and supermarkets expect a decrease in market share while discount stores expect an increase. Within Danish grocery retailing, discount stores have gained market share since the global financial recession in 2008–2009, and franchise-based retail stores in particular have experienced large increases in market share both nationally and locally (e.g. city and neighbourhood). One reason for this is that franchise-based discount stores have managed to meet consumer requirements at both the national chain and local store levels. Convenience and speciality stores typically sell higher priced/ more expensive products and are thus often not the primary sales channel for consumers' grocery shopping.

Figure 1-1. Market share of European grocery retailing for the six main sales channels, in 2018 and 2023 (The Institute of Grocery Distribution, 2019)



The increasing market size and growth of the FFPs, coupled with the increasing focus on food waste, results in a potentially larger economic impact if not fulfilling the growing consumer requirements. This makes the availability of fresh products in retail stores at the time of consumers' shopping ever more important for FFP supply chains. Thus, this PhD study focuses on the retailing of FFPs.

1.2. FRESH FOOD PRODUCT CHARACTERISTICS

Fresh food retailing is characterised in a specific manner, entailing special logistical requirements at product category level in the supply chain, such as temperature control and product traceability (Entrup, 2005; Fredriksson and Liljestrand, 2015; Romsdal, 2014). These so-called planning environment characteristics (PECs) challenge conventional supply chain practices (Blackburn and Scudder, 2009; Kuhn and Sternbeck, 2013; Nakandala and Lau, 2019). The following outlines the most noteworthy PECs.

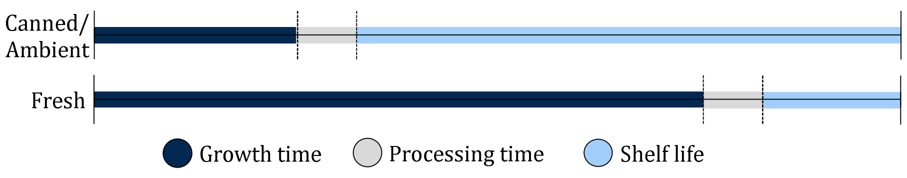
One of the most distinct PECs is perishability. This relates to the degradation of product quality over time, until of no value and potentially harmful for human consumption. To slow down this process (i.e. extending shelf life), FFPs are handled/stored in temperature-controlled environments (above freezing point/point of chilling injury) (Evans, 2016; Man, 2016). Yet still, some FFPs have only a few days shelf life (from processing to expiration), with rapid degradation curves (Cengel and Ghajar, 2015; Evans, 2016). Hence, inventory building to meet demand may be limitedly appropriate, if at all (Taylor and Fearne, 2009). Thus, FFPs are delivered more frequently across the supply chain in order to avoid undersupply (out-of-stock and lost sales) and oversupply (reduced quality and waste). In addition, markdown strategies control and adjust the demand and level of food waste (Buisman et al., 2019; Holweg et al., 2016; Hübner et al., 2013).

FFPs are also characterised by demand seasonality, where certain products are only/particularly requested during specific periods of the year. This, combined with the use of campaigns, causes significant fluctuations and uncertainty in demand signals throughout the supply chain. Studies on product groups indicate upwards of ±11% variation around mean demand in retail stores and up to ±115% at the supplier stage (Taylor and Fearne, 2009). Related to this is supply seasonality. Raw materials used for FFPs may only (limitedly) be available during specific periods of the year. As a result, raw materials are stored upstream at low temperatures in quantities reflecting expected demand, in order for there to be enough raw material to meet demand in periods when they are otherwise unavailable.

Additionally, in terms of raw material availability, most FFPs, such as meat, fish, fruit and vegetables, derive from living animals/plants where the size, weight and shape typically vary from batch to batch (Entrup, 2005). Moreover, quality, capacity and/or yielding/harvesting of products or raw materials as well as indefinite growth time of raw materials (e.g. fish) may vary (Christensen et al., 2017a; Ferguson and Koenigsberg, 2007). This results in a latent uncertainty of raw materials availability. Based on experience and historical availability, the FFP processors (and their suppliers, i.e. farmers) circumvent this by considering an additional amount of raw material (corresponding to unavailability) in their planning of slaughtering and breeding animals. Hence, if e.g. fish are smaller during winter than summer, an additional quantity reflecting this residual is added during winter. From a wholesaler point of view, to ensure availability of the ready FFPs, multi-sourcing is typically used when possible (often constrained by the specialised processing, i.e. few FFP processors).

In parallel with this, FFPs are characterised by an almost inverse relationship of products' lifetime (growth time, processing time and shelf life) compared to other food products (Christensen et al., 2017a) (see Figure 1-2). The majority of canned, ambient and dry products have a relatively short growth time compared to shelf life, which may be up to several years. Conversely, FFPs have a growth time of up to a few years though only a few days shelf life.

Figure 1-2. Lifetime of different product groups (Christensen et al., 2017a)



Since the accuracy of forecasting is affected by the time-horizon of the forecast, the shorter the time-horizon, the greater accuracy and reliability of the forecast, hence lower risk and fewer errors (Hanke and Wichern, 2009). However, FFPs are influenced by scarcity when the time required to produce raw materials for slaughtering exceeds the forecast horizon. As a result, the demand planning (i.e. forecast) must be closely related to supply planning (i.e. replenishments), since raw materials are living animals with different growth times. An example of the growth time for fresh meat products is provided in Table 1-1.

Table 1-1. Age and size of animals before they are ready for slaughtering and catching (Christensen et al., 2017a)

Beef	Pork	Chicken	Fish
<10 months (veal) 10–24 months (young cattle) >24 months (cow-beef)	≈ 5–6 months (90–105 kilos)	≈ 40 days	>40–60* cm (salmon) >25–27* cm (flounder) >30–35* cm (cod)

*Depends on area (e.g. North Sea, Baltic Sea, Kattegat) and habitat (salt- or freshwater).

1.3. CHALLENGES IN FRESH FOOD RETAILING

High consumer requirements, particularly regarding product availability, quality (i.e. freshness) and price, challenge fresh food retailing (Hübner et al., 2013; Jacobsen and Bjerre, 2015). Product availability (also known as on-shelf-availability) refers to the availability of a desired product in an acceptable condition on the shelf and being ready for purchase when the consumer wants it (Ettouzani et al., 2012). The level of availability may be defined as "the fraction of demand that is served on time from product held in inventory" (Chopra and Meindl, 2010, p. 67).

Product availability has been studied for decades (Aastrup and Kotzab, 2010; Moussaoui et al., 2016), and previous studies report up to 99% availability in retail stores, where FFPs range between 93.4 and 98.5%, depending on the type of FFP (e.g. diary, fresh produce, meat, bread, etc.) (Aastrup and Kotzab, 2009; McKinnon et al., 2007). However a more recent study from the industry shows that 68% of consumers feel disappointed with product freshness and 81% experience not being able to find the product they want when they want it (i.e. out-of-stock (OOS)), resulting in the fact that 20% of shoppers "have stopped shopping with the retailer either permanently or for a period of time" (BlueYonder, 2017, p. 18).

> **Out-of-stock:** "a product not found in the desired form, flavour or size, not found in saleable condition, or not shelved in the expected location."
>
> (ECR Europe, 2003, p. 8)

The challenge of OOS has also been studied during the past decades and is a well-known phenomenon in the grocery retailing industry (Aastrup and Kotzab, 2010; Corsten and Gruen, 2003; Gruen et al., 2002). A global study by Gruen et al. (2002) investigated the causes of OOS situations. Table 1-2 illustrates the percentwise distribution. In total, retail stores account for 70% of OOS situations while supply chain accounts for 30%. Although better than the global average (72%), 53% of OOS situations in Europe relate to poor replenishment across the supply chain, i.e. timing and sizing of orders according to forecasted demand.

Table 1-2. Out-of-stock causes Globally and in Europe (Gruen et al., 2002)

Out-of-stock cause	Europe	Global average	Responsible
Store ordering*	*11%*	*13%*	*Retail store*
Store forecasting*	*22%*	*35%*	*Retail store*
Ordering	***32%***	***47%***	
Store stocking	*38%*	*25%*	*Retail store*
Warehousing*	*9%*	*10%*	*Supply chain*
Replenishment	***47%***	***35%***	
Management*	*11%*	*14%*	*Supply chain*
Others	*10%*	*4%*	*Supply chain*
Planning	***21%***	***18%***	

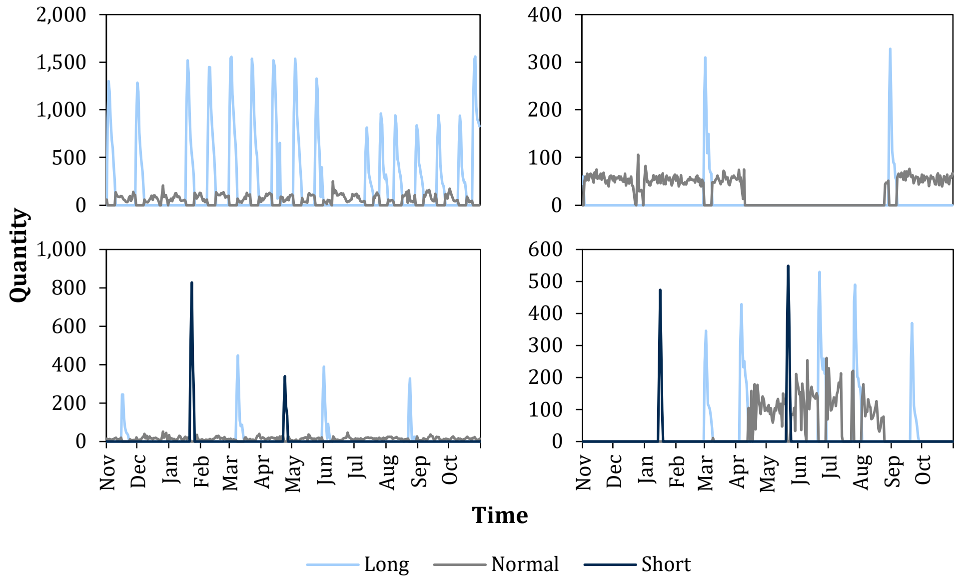
*Related to the planning and control of replenishments.

Increasing the product availability, hence reducing OSS, is in itself a rather straightforward task if merely building inventories and ignoring associated costs (e.g. ordering, carrying and capacity costs). However, FFPs rapidly decrease in quality and thus a further increasingly important challenge is food waste.

Food waste features on climate agendas around the world. Food waste has a double climatic impact, as it influences the environment not only during production but also through the treatment of food waste (Stenmarck et al., 2011). Additionally, cost per tonne of edible food waste is higher at the downstream of the value chain (Stenmarck et al., 2016), reducing the profit base (Hübner et al., 2013). Global food waste along the supply chain has been reported to be around one-quarter of processed food and upwards of one-third of harvested raw material (Kummu et al., 2012; Mena et al., 2014; Parfitt et al., 2010), constituting hundreds of billions of EUR in economic, environmental and social costs annually (Fattibene and Bianchi, 2017). A large amount of food waste is accredited to FFPs, upwards of 95% depending on the country (Parfitt et al., 2010). In Danish grocery retailing, more than 172,000 tonnes of consumable food products are wasted each year, equivalent to 3,000 full shopping carts *every* day (Stenmarck et al., 2016). Thus, while the OOS situations imply a shortage in supply, food waste implies an excess of supply.

Further, over time large corporations have emerged in grocery retailing and have started and/or acquired different retail chains, resulting in a very high level of competition in some countries. In Danish grocery retailing, six corporations (Reitan Distribution, Salling Group, COOP, Dagrofa, Lidl and Aldi) supply products to almost 20 different grocery retail chains (Retail Institute Scandinavia, 2017). As a result of this, coupled with low consumer loyalty to retail stores/chains (Jacobsen and Bjerre, 2015), a heavy focus on campaigns and promotions characterises the market. Some retail chains have more than 100 campaigns per year, some long (7 days) and other shorter (3–4 days). This influences demand, and Figure 1-3 illustrates how demand for four FFPs fluctuates as a result of campaigns in retail stores in a Danish retail chain. Normal demand refers to products not sold at a reduced campaign price and thus includes, e.g. regular, seasonal and holiday sales. Campaign demand refers to products sold at a reduced price either through campaign(s) or by promotion. In addition to this, the demand for FFPs is also influenced by other factors, such as weather, temperature and season (Stenmarck et al., 2011).

Figure 1-3. Demand fluctuation in retail stores due to campaigns



Some studies suggest that a straightforward approach to circumvent these challenges is to e.g. narrow the product assortment in order to increase the demand for the individual product or enforce a "every-day-low-price" policy, since either will enhance demand stability (Taylor and Fearne, 2009; van Donselaar et al., 2006). Although discount retail chains have managed to lower prices on a permanent basis by selling few products with large demand, the demand is still impacted by the heavy use of campaigns and promotions. Thus, strictly offering a narrow assortment without the (additional) reduction of prices from campaigns counteracts the exact consumer requirements for product assortment and price which prevail in competitive fresh food/grocery retailing.

Other studies suggest increasing the supply chain co-operation through collaborative planning and replenishment, in order to ensure effective replenishment decision-making with a subsequent *increase* of information sharing (Kembro and Näslund, 2014; van Donselaar et al., 2010). Several so-called automatic replenishment programs (ARPs) entail this, where sales rather than forecasts and safety stocks (automatically) drive replenishment (Myers et al., 2000; Sabath et al., 2001; Stank et al., 1999). In fact, studies illustrate or suggest that the automatic order timing and sizing of perishable products improves product freshness and reduces waste (see e.g. Kiil et al., 2018a, 2018b; Mena et al., 2011). This mainly accepts the premise that increasing the remaining shelf life in stores by one day results in improved freshness, availability and waste levels (Broekmeulen and van Donselaar, 2017).

> **Automatic replenishment program:** "all programs in which inventory restocking is triggered by actual sales rather than relying upon long-range forecasts and safety stock buffers."
>
> (Sabath et al., 2001, p. 91)

However, studies indicate that a main reason for waste, namely implicitly reduced freshness, relates not only to inventory control but also demand forecasting (de Moraes et al., 2020; Mena et al., 2014; Teller et al., 2018). Thus, current challenges in fresh food retailing place high requirements on the effective information sharing and order decision-making regarding demand forecasting and the subsequent timing and sizing of replenishments. Henceforth, this is referred to as "replenishment planning and control" (RP&C). Effectiveness relates to high availability and freshness with low waste and inventory, by reducing under- and oversupply (Eriksson et al., 2014; Mena et al., 2014).

> **Replenishment planning and control:** the operational planning and control of inventory replenishments in supply chains, where planning relates to demand forecasting, control to the timing and quantity of replenishments and the focus is on information sharing between supply chain stages.

1.4. CURRENT APPROACHES IN FRESH FOOD REPLENISHMENT

Since the 1990s, several different ARPs encompassing RP&C have evolved, mainly differing from one another in their planning horizons (long vs short), information sharing (from just the order to long-term strategic information) and levels of collaboration (from separated to buyer-/supplier-dominated to collaborative). The programs include e.g. Efficient Replenishment (ER) (Kurt Salmon Associates, 1998), Vendor-Managed Inventory (VMI) (Ståhl Elvander et al., 2007), Collaborative Planning, Forecasting and Replenishment (CPFR) (VICS, 2004) and Collaborative Buyer-Managed Forecasting (CBMF) (Alftan et al., 2015) – with some programs developed specifically for grocery retailing (e.g. ECR and CBMF). However, despite their different levels of collaboration and information sharing, poor forecasting and order decision-making remain a challenge (de Moraes et al., 2020; Mena et al., 2014; Teller et al., 2018). There are a number of challenges hindering a complete grasp of the FFPs' PECs in terms of the RP&C, as discussed in the following.

The ARPs are complex to implement in practice and there is little knowledge of their effect on performance, or of what actually creates a possible effect (Jonsson and Holmström, 2016). There is generally limited implementation of ARPs (Mena et al., 2014) due to e.g. cost-heavy involvement of resources (e.g. CPFR) (Alftan et al., 2015; Whipple and Russell, 2007). Some programs even remain at the conceptual stage (e.g. CBMF), without further empirical evidence (Alftan et al., 2015). Further, ARPs are applied at product group level, usually for a specific demand type or supplier. As an example, VMI is suggested for products with stable demand, CPFR for strategic products with relatively fluctuating demand and CBMF for products with volatile demand requiring exception management (Alftan et al., 2015; Kaipia and Holmström, 2007). As discussed in the prior section, fresh food (and grocery) retailing is heavily influenced by campaigns and promotions. Thus, the static nature of the ARP (i.e. one ARP for one type of demand, another ARP for a different type) seems to entail switching between the ARPs, depending on the demand type in order to fully realise the benefits.

In relation to information sharing in FFP supply chains, wholesaler and retail stores should provide demand information to FFP processors (Nakandala et al., 2017). For perishable supply chains in particular, "the shorter the shelf life of the product (the more perishable), the stronger the positive relationship between information sharing and perishable product supply chain performance" (Lusiantoro et al., 2018, p. 276). However, studies focusing on ARPs provide limited recommendations about which information to share, and when and how to do so. The studies generally entail sharing the same information for all products in the same way. For example, point-of-sales (POS) data is information which is often-hyped and which is recommended to be shared for all products in all ARPs. Further, the ARPs entail replenishment information sharing with the same pre-agreed timing for all FFPs, e.g. "when the actual inventory levels and retailers' orders are known" (Alftan et al., 2015, p. 244) or when inventory levels reach a certain point (Kiil et al., 2018a). Hence, the timing is differentiated at FFP processor level or by specific demand characteristics (Alftan et al., 2015; VICS, 2004) and is thus demand-driven. For supplier-managed ARPs such as e.g. (advanced) VMI, it is even a premise to let the supplier have full visibility of downstream information by continuously sharing information (Ståhl Elvander et al., 2007). This is the case despite the fact that upstream supply chain stages struggle to understand and utilise the POS data (Narayanan et al., 2019; Raman et al., 2001).

Information sharing in itself does not automatically improve performance (Baihaqi and Sohal, 2013). Sharing too much or irrelevant information (Choi et al., 2013), or sharing information too early or too late (Xu et al., 2015), may cause losses related to e.g. forecast errors and different incentives between suppliers and buyers. Rather than sharing the same information for all products at the same time in the same way, it may be beneficial to differentiate the information sharing at a lower level (Huang et al., 2003). Thus, effective information sharing should differentiate and reflect the PECs rather than being automated according to general inventory rules (e.g. order-up-to level (Kiil et al., 2018a)) and remaining the same across products and supply chains (Nakandala et al., 2017). Phrased in a different way: "share only information that improves supply chain performance" (Kaipia and Hartiala, 2006, p. 385).

For order decision-making, the application of mere automatic (replenishment) decision-making in ARP has led to the inefficient utilisation of processes due to a misalignment between cost-profit objectives and users' incentives, with inadequate consideration of demand seasonality and demand forecasting parameters (van Donselaar et al., 2010). This occurs despite the fact that different heuristics are suggested for inventory control of FFPs, as they have practical relevance, resemblance and applicability with up to 17.7% increased availability or 10.7% waste reduction (Broekmeulen and van Donselaar, 2009; Duan and Liao, 2013; Kiil et al., 2018b). However, they take only demand type (normal or campaign), demand variation or shelf life into consideration, and not the impact of e.g. out-of-stock situations.

Given the shortcomings in current ARPs' information sharing and order decision-making in RP&C, and the challenges in applying any 'one-fit-all' approach for FFPs without considering their intrinsic differences, the RP&C should encompass the PECs at a product level. This should be done to the extent that FFPs which are similar across selective PECs are planned and controlled in the same manner.

1.5. RESEARCH OBJECTIVE

This research seeks to contribute to both practice and academia, based on the outlined challenges in fresh food retailing and current approaches to solving these challenges. It considers RP&C to the extent of order decision-making (demand forecast and inventory control) and information sharing across the supply chain, operationalised through two research questions: one for information sharing and one for order decision-making.

> **Objective:** The objective is to contribute to how the planning environment characteristics may be reflected in the design of effective replenishment planning and control, i.e. order decision-making and information sharing. Effectivity relates to high availability and freshness with low waste and inventory.

Information sharing supports decision-making and is a vital part of replenishment planning and control. It is considered a pivotal remedy to reduce under-/oversupply (e.g. Lusiantoro et al., 2018) and the bullwhip effect (Disney and Towill, 2003a). Effective information sharing is sharing the *right* information, with the *right* parties, at the *right* place *and* time, in the *right* way and under the *right* circumstances (Huang, Lau, and Mak 2003; Kembro and Näslund 2014). Ineffective information sharing may induce losses in the supply chain (e.g. Xu et al., 2015). Despite this, wholesaler and retail stores seem reluctant to share information due to e.g. size/power imbalances with suppliers which can cause opportunistic behaviour (Kähkönen and Tenkanen, 2010; Nakandala et al., 2017) and/or the perceived risk of inappropriate utilisation by suppliers (Huang et al., 2018; Narayanan and Raman, 2004), or dishonesty (Heese and Kemahlioglu-Ziya, 2016).

Information sharing is extensively studied (e.g. Kembro et al., 2014). Studies suggest that information sharing be based on an "understanding of all the supply chain attributes rather than relying on generalizations" (Nakandala et al., 2017, p. 114). One supply chain stage which seems to have an understanding of the divergent and convergent flows of information and products in the supply chain is the wholesaler or distribution centres, since they link FFP processors with retail stores (Alftan et al., 2015; Hübner et al., 2013). Thus, to adequately understand PECs and investigate how they can affect information sharing and order decision-making during effective RP&C, two main questions are posed. In answering RQ1, two additional sub-questions are posed, in order to identify and characterise PECs and information sharing in FFP grocery retailing.

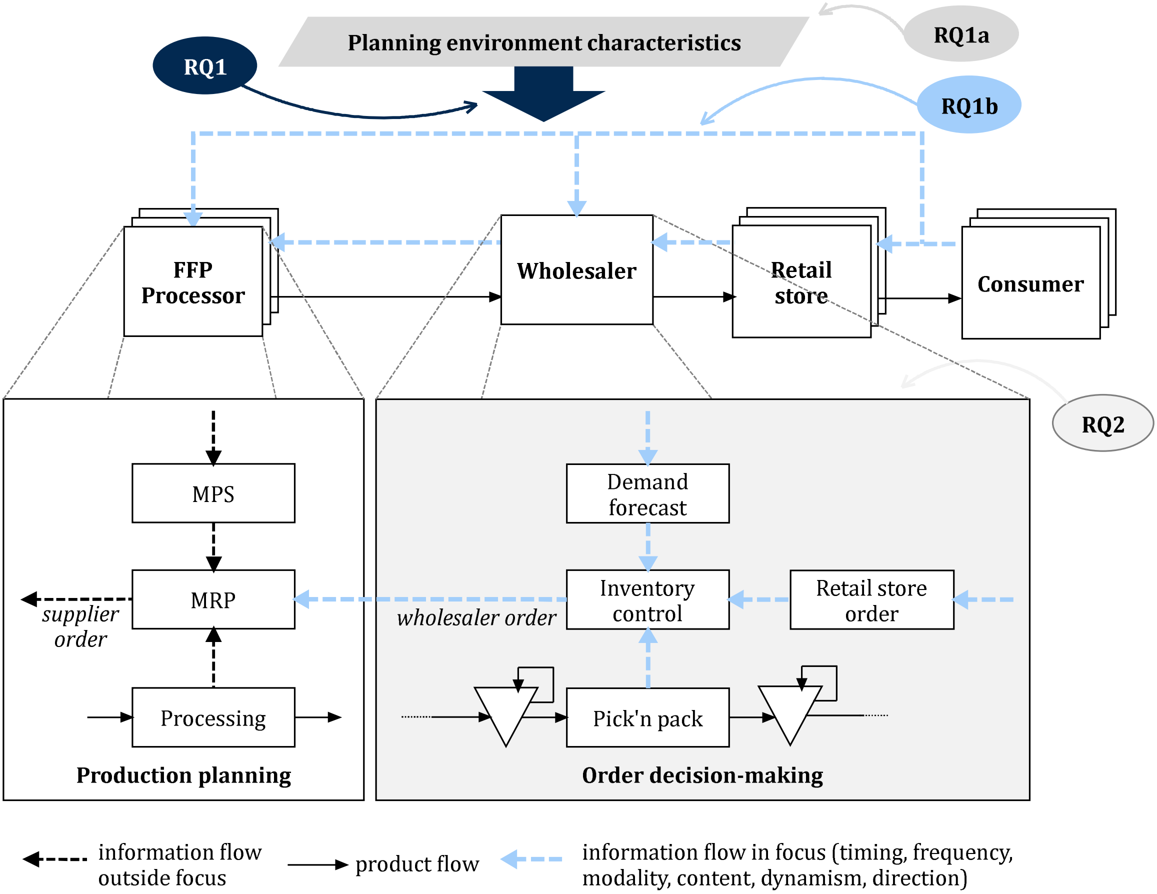
> **RQ1**: How do planning environment characteristics impact information sharing during replenishment planning and control in fresh food retailing?
>
> > **RQ1a:** What are the planning environment characteristics in fresh food retailing, and how are they characterised?
> >
> > **RQ1b:** How is information sharing during replenishment planning and control in fresh food retailing characterised?
>
> **RQ2**: How can wholesaler effectively plan and control replenishments according to the fresh food planning environment characteristics, and what is the impact on performance?

The research questions build on the recognition of PECs, and it is thus hypothesised that information sharing during RP&C of FFPs should be product-specific, bounded by the individual product's PECs and derived from a contextual premise. Hence, this research differs from today's group-level identification of contextual premises based on general observations by employing a product-level identification based on the individual FFP, thereby encompassing the intrinsic differences of FFPs.

Thus, RQ1 explores how PECs and information sharing during RP&C is characterised in fresh food retailing, in order to advance the current understanding of PECs' impact on information during RP&C. Based on this, RQ2 normatively seeks to propose solutions for ensuring effective RP&C of FFPs while considering PECs. The theoretical knowledge leads to ex ante hypotheses for testing in order to generate new theory (deductive) while the empirical knowledge leads to hypotheses or propositions without testing (inductive).

The relationship between the research questions in relation to the scope is depicted in Figure 1-4, which illustrates the area each research question address, where the dark grey represents PECs in fresh food retailing (RQ1a), blue represents information sharing in the supply chain (RQ1b), dark blue represents the impact of PECs on information sharing (RQ1) and grey represents the order decision-making (RQ2). The full black arrows represent the flow of FFPs, the dashed black arrows represent information flow outside the focus of this PhD study and the dashed blue arrows represent the information flow to the RP&C in focus during this PhD study.

Figure 1-4. Overall research framework



1.5.1. SCOPE

To specify the direction of this research and delineate its positioning, further positioning in terms of literature streams and terminologies is needed. Overall, any technical, technological, financial and economic factors are delimited during the normative solution phase of this study, although they are acknowledged when appropriate during the exploratory analysis phase. Considering the focus on FFPs, secondary and tertiary literature streams related to non-perishable items are delimited. This is particularly due to the impact of perishability and the consequent inappropriate exclusion of quality degradation through time when seeking other literature streams to fulfil consumer requirements, e.g. for availability.

From a supply chain perspective, the focus is on the last part of the FFP supply up until point-of-sale (POS). There is generally limited focus on wholesalers in the literature (Fredriksson and Liljestrand, 2015). Therefore, this project focuses on wholesaler, considering their crucial role in conveying FFPs from processor to retail store (so that they are available to the consumer) (Hübner et al., 2013). Further, the nature of this research study (i.e. industrial PhD project) affects the focus. In terms of the RP&C activities, the focus is specifically on the internal RP&C at wholesaler and retail stores and the linked information sharing between FFP processors, wholesaler and retail stores. Hence, unless explicitly addressed, this study does not include FFP processors' internal production planning and control, nor order decision-making in retail stores.

From a RP&C perspective, specifically for information sharing, although the quality of information is an often-highlighted factor to consider (see e.g. Jonsson and Myrelid, 2016; Myrelid and Jonsson, 2019), this study assumes that the information is readily available in high quality and that it can be handled and utilised without any influence from any internal/external factors not considered explicitly. A main part of RP&C relates to answering the question of when to replenish, entailing a focus on forecasting FFP demand. While on the one hand forecasting relates to the qualitative/quantitative/mix models for predicting future demand, on the other hand it relates to the evaluation of the models. This study is delimited from investigating the actual forecasting models. Instead, focus is on the evaluation of the forecasting models. In terms of inventory control, this study delimits from models introduced for perishable products with fixed or random shelf life and fixed or continuous review periods modelling deterministic or stochastic demand (Bakker et al., 2012; Goyal and Giri, 2001; Raafat, 1991; Silver et al., 1998; Steven Nahmias, 1982). Since heuristics are reported to have improved conditions for implementation and applicability in real life (Broekmeulen and van Donselaar, 2009; Duan and Liao, 2013; Kiil et al., 2018b), this study focus on heuristics related to perishable products.

1.6. THESIS OUTLINE

The remainder of this dissertation is structured around six chapters as illustrated in Table 1-3. First, the theoretical background is presented (Chapter 2), followed by the applied research design (Chapter 3), the findings and discussion (Chapters 4 and 5) and finally the conclusion (Chapter 6).

Table 1-3. Structure of the dissertation according to the research questions

Area	RQ1	RQ2
Theoretical background	Section 2.2 + 2.3	Section 2.4
Research design	Section 3.1.1	Section 3.1.2
Findings and discussion	Chapter 4	Chapter 5
Conclusions	Chapter 6	Chapter 6
Appended papers	1–5	6–9

This dissertation is based on the research conducted and documented in the nine articles and conference proceedings below, and aims to synthesise and present these results. The thesis is intended to be read and understood without reading the appended papers, with references made to the individual papers when appropriate and clarification of details may be needed.

Paper #1

Christensen, Flemming M. M., Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2017b. "Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime." In *Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing – Proceedings, Part II*, pp. 139–147.

Paper #2

Christensen, Flemming M. M., Jonsson, Patrik, Dukovska-Popovska, Iskra, and Steger-Jensen, Kenn. 2019. "Information Sharing for Replenishment Planning and Control in Fresh Food Supply Chains: A Planning Environment Perspective." To be submitted to *Production Planning & Control* for third review, October 2020.

Paper #3

Christensen, Flemming M. M., Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2017a. "Replenishment Planning of Fresh Meat Products: Case Study from a Danish Wholesaler." In *Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing – Proceedings, Part II*, pp. 130–138.

Paper #4
Mantravadi, Soujanya, Møller, Charles and Christensen, Flemming M. M. 2018. "Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration." In *International Conference on Smart Systems and Technologies (SST): IEEE Region 8*, Croatian Academy of Engineering, pp. 133–137.

Paper #5
Christensen, Flemming M. M., Mantravadi, Soujanya, Dukovska-Popovska, Iskra, Hvolby, Hans-Henrik, Steger-Jensen, Kenn and Møller, Charles. 2019. "Horizontal Integration in Fresh Food Supply Chain." In *Advances in Production Management Systems, Production Management for the Factory of the Future – Proceedings, Part II*, pp. 164–172.

Paper #6
Christensen, Flemming M. M., Bojer, Casper S., Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2019. "Developing New Forecasting Accuracy Measure Considering Product's Shelf Life: Effect on Availability and Waste." Submitted to *Journal of Cleaner Production* for third review, September 2020.

Paper #7
Christensen, Flemming M. M., Steger-Jensen, Kenn and Dukovska-Popovska, Iskra. 2017. "Product Characteristics for Differentiated Replenishment Planning of Meat Products." In *International Symposium of Logistics*, ISL, pp. 594–601. Ljubljana.

Paper #8
Christensen, F. M. M., Steger-Jensen, K. and Dukovska-Popovska, I. 2020. "Managing Perishable Multi-Product Inventory with Supplier Fill-Rate, Price Reduction and Substitution." In *Advances in Production Management Systems, Towards Smart and Digital Manufacturing – Proceedings, Part II*, pp. 640–649.

Paper #9
Christensen, Flemming M. M., Meldgaard, Jens Peder, Jonsson, Patrik, Dukovska-Popovska, Iskra and Steger-Jensen, Kenn. 2020. "Real-Time Point-of-Sales Information Sharing in Fresh Food Supply Chain." To be submitted to *International Journal of Production Economics* for first review, October 2020.

During the PhD research study, two additional papers were authored and have provided input for various parts of the PhD research study: Paper #A1 (not directly related to the objective of the thesis) and Paper #A2 (extended to a journal publication, Paper #6).

Paper #A1
Bojer, Casper Solheim, Dukovska-Popovska, Iskra, Christensen, Flemming M. M. and Steger-Jensen, Kenn. 2019. "Retail Promotion Forecasting: A Comparison of Modern Approach." In *Advances in Production Management Systems, Production Management for the Factory of the Future – Proceedings, Part I*, pp. 575–582.

Paper #A2
Christensen, Flemming M. M., Dukovska-Popovska, Iskra, Bojer, Casper S. and Steger-Jensen, Kenn. 2019. "Asymmetrical Evaluation of Forecasting Models through Fresh Food Product Characteristics." In *Advances in Production Management Systems, Production Management for the Factory of the Future – Proceedings, Part II*, pp. 155–163. (Awarded the "John Burbidge Best Paper Award 2019".)

2

THEORETICAL BACKGROUND

To ensure theoretical relevance and positioning, relevant literature streams were investigated and examined before and in parallel with each sub-study. This chapter presents and outlines the combined theoretical foundation for this PhD study, divided into five sections, and introduces the terms used in this study.

Section 2.1 provides a brief and general introduction to current automatic replenishment programs (ARPs) in grocery retailing, which encompass replenishment planning and control (RP&C) from a wholesaler-application point of view.

Next, Section 2.2 presents the theoretical background for RQ1a, planning environment characteristics (PECs). Attention is given to the current understanding of product, demand, supply and production, as it is expected that these will have a direct impact on the RP&C of fresh food products (FFPs). While demand and supply characteristics reflect the essence of RP&C in terms of balancing demand and supply, the product and production characteristics reflect the uniqueness of FFPs in terms of intrinsic product characteristics and being able to ensure supply of FFPs in the first place. Following this, Section 2.3 presents the theoretical background for RQ1b, information sharing. Attention is given to the different facets of information sharing, as these will allow a multi-dimensional understanding of how often, when, with whom, about what and how to share information, as well as when to share, considering changes in PECs.

Finally, Section 2.4 presents the theoretical background for RQ2, order decision-making. Attention is given to the current understanding of demand forecast evaluation and subsequent inventory control, as these two areas are expected to support order decision-making, which reflects the essence of RP&C. Both areas are reflected in the context of FFPs.

To allow for the evaluation and comparison in this PhD study, Section 2.5 presents different key performance evaluation criteria relevant for the context of FFPs. Section 2.6 provides a summative overview of the literature in relation to the research questions, i.e. the applied research framework for this study.

2.1. REPLENISHMENT PLANNING AND CONTROL IN AUTOMATIC REPLENISHMENT PROGRAMS

For decades, various programs for information sharing and order decision-making have been proposed to improve the supply chain. These are often referred to as, automated replenishment (programs) (Myers et al., 2000; Sabath et al., 2001; Stank et al., 1999), collaborative materials management (Jonsson and Holmström, 2016), retailer-supplier relationships (Simchi-Levi et al., 2003), ordering and replenishment practices (Pramatari and Miliotis, 2008) or collaborative (replenishment) strategies (Derrouiche et al., 2008; Kamalapur et al., 2013).

Some of the most known programs within grocery retailing are efficient replenishment (ER), continuous replenishment (CR), vendor managed/owned inventory (VM/OI), the process of collaborative store ordering (PCSO), collaborative buyer-managed forecasting (CBMF) and collaborative planning, forecasting and replenishment (CPFR). Each of these overcome the limitations of traditional arms-length replenishment (TR) in different ways, and each of these are discussed in the following in terms of information sharing and order decision-making (i.e. demand forecast and inventory control). Although certain programs reflect other planning areas and horizons (e.g. CPFR: strategic and tactical), this is omitted in the following given the focus on RP&C. Further, information about e.g. assortment and new products added, minimum order quantities and product replacements/substitutions is omitted, since this is commonly shared in order for all programs to initiate RP&C in the first place.

2.1.1. EFFICIENT & CONTINUOUS REPLENISHMENT

As a pendant to the textile industry's Quick Response, ER was formalised as part of the holistic planning framework, Efficient Consumer Response, in the early 1990s (Kurt Salmon Associates, 1998, 1993). ER aims to make the supply chain work "together as business allies to reduce total system costs, inventories and physical assets while improving consumers' choice of high-quality fresh products" (Derrouiche et al., 2008, p. 429). More specifically, ER attempts to lower the costs associated with e.g. order processing (e.g. paper work, order lead-time, order evaluation), ordering errors and inventory (in relation to sales) (Brown and Bukovinsky, 2001; Dong et al., 2007). In ER, the focus is on "expediting the quick and accurate flow of information up the supply chain" (Lummus and Vokurka, 1999, p. 13).

A further development of ER is CR (Lummus and Vokurka, 1999), where suppliers "prepare shipments at previously agreed-upon intervals to maintain specific inventory levels" (Simchi-Levi et al., 2003, p. 154). Bounded by an "every-day-low-price" approach (Raghunathan and Yeh, 2001), CR advanced ER by allowing suppliers to synchronise production with actual sales, in turn generating a higher replenishment frequency and thereby continuous flow of products. This is based on the premise that efficient production of smaller quantities (hence also inventory levels) outweighs the impact of reduced lead-time. Further, the more steady and reliable wholesaler orders are, the greater is the ability to optimise production at suppliers, which subsequently improves the ability of producing smaller quantities (Fisher and Raman, 2010).

Some studies suggest that variations of ER/CR where suppliers are in charge of replenishments (according to pre-agreed ranges of inventory levels) essentially reflect the program of VMI and thus eliminates the order sharing from wholesaler (Brown and Bukovinsky, 2001; Reyes and Bhutta, 2005). Others suggest that ER/CR entails that wholesaler remains the order decision-makers, thereby delineating ER/CR from VMI (Sabath et al., 2001). In this PhD study, both ER and CR entail wholesaler being in charge of the order decision-making, with a distinction in terms of encompassing any demand, including campaigns/ promotions (ER) vs stable demand with no campaign/promotion (CR).

2.1.2. VENDOR MANAGED/OWNED INVENTORY

Emerging in the late 1980s, VMI entails that suppliers are better capable of forecasting future demand and replenishing wholesaler's inventory (van Hoek and Harrison, 2008). In this way, the order decision-making changes from wholesaler being responsible for inventory to merely renting space for supplier-replenished inventory, merely entailing transactions within already established agreements (Zammori et al., 2009). The most distinct variation of VMI is VOI, where ownership of the products also changes: from wholesaler to suppliers. Thus, while VMI entails suppliers' ownership until the product has arrived at the wholesaler's stock, VOI entails suppliers' ownership until the product is sold from the wholesaler's stock. Both VMI and VOI imply that suppliers are "responsible for all decisions regarding product inventories" regarding wholesaler (Chopra and Meindl, 2010, p. 502), (hereafter order quantities), manner of transport and timing for replenishments (Sabath et al., 2001).

The VMI program has various derivatives depending on the level of sellers' responsibility, collaboration and information sharing. These include e.g. re-seller managed inventory, supplier managed inventory, retailer managed inventory, distributor managed inventory, vendor managed replenishment, jointly managed inventory, co-managed inventory, co-managed replenishment and supplier owned inventory. Further, literature considers VMI differently as to whether it is an 'individual' program or e.g. part of ER or CR, an alternative to CR or CPFR or the same as CR (Marquès et al., 2010). For reasons of simplicity, this study considers VMI and VOI as individual programs, distinguished only by the point of ownership with the highest level of advancement and trust.

2.1.3. COLLABORATIVE PLANNING, FORECASTING AND REPLENISHMENT & THE PROCESS OF COLLABORATIVE STORE ORDERING

Developed in the 1990s, CPFR is one of the most comprehensive and developed planning programs (Attaran and Attaran, 2007). It initially started as pilotproject called collaborative forecasting and replenishment. CPFR expands previous programs by establishing formally agreed upon business processes regarding cooperating around the planning, forecasting and replenishment aspect (VICS, 2010, 2004). In this way, CPFR goes beyond day-to-day guidance by "making long-term projections which are constantly updated based on actual demand and market changes" (Stank et al., 1999, p. 75). In CPFR, the supplier and wholesaler agree upon the product assortments and together plan the (campaign) events for the forthcoming planning period.

Since CPFR is considered a program between suppliers and wholesaler, given its extensive collaborative planning, PCSO is suggested as a lighter alternative that allows for the inclusion of retail stores (Pramatari and Papakiriakopoulos, 2002). In PCSO a collaborative replenishment process between suppliers and retail stores allows direct communication and knowledge flow between the suppliers and retail stores, while leaving wholesaler in charge of the physical replenishment (ensuring efficient utilisation of e.g. logistics). The supplier generates an order proposal through an internet-based platform which retail stores can reject, adjust or directly accept. Once accepted, the order is shared with wholesaler and suppliers, followed by delivery to wholesaler and further to retail stores.

2.1.4. COLLABORATIVE BUYER-MANAGED FORECASTING

One of the latest planning programs is CBMF, which aims to combine VMI and CPFR and overcome the challenges particularly related to promotions, campaigns and product introductions. CBMF entails a centralised order forecast generated by the most capable supply chain in terms of skills, interest and knowledge. Then, "the order forecast that is created serves both base-level forecasting and exception management" (Alftan et al., 2015, p. 244), with a VOI approach between suppliers and wholesaler and a VMI approach between wholesaler and retail stores. Considering the wholesaler to be most capable, CBMF allows a better understanding of downstream demand for suppliers, resulting in better management of promotions, campaigns, seasons, introductions and exceptions (e.g. local events).

2.1.5. COMPARATIVE OVERVIEW OF THE PROGRAMS

Several planning programs are suggested for RP&C in grocery retailing and Figure 2-5 summarises the responsibility areas of suppliers and wholesaler in terms of governance areas, considering both the information and product flow between the two. Five different constellations reflect the programs, with (1) representing TR, ER and CRP, (2) VMI and VOI, (3) CBMF, (4) CPFR and (5) PCSO.

Figure 2-5. Distribution of responsibility areas during RP&C in ARPs

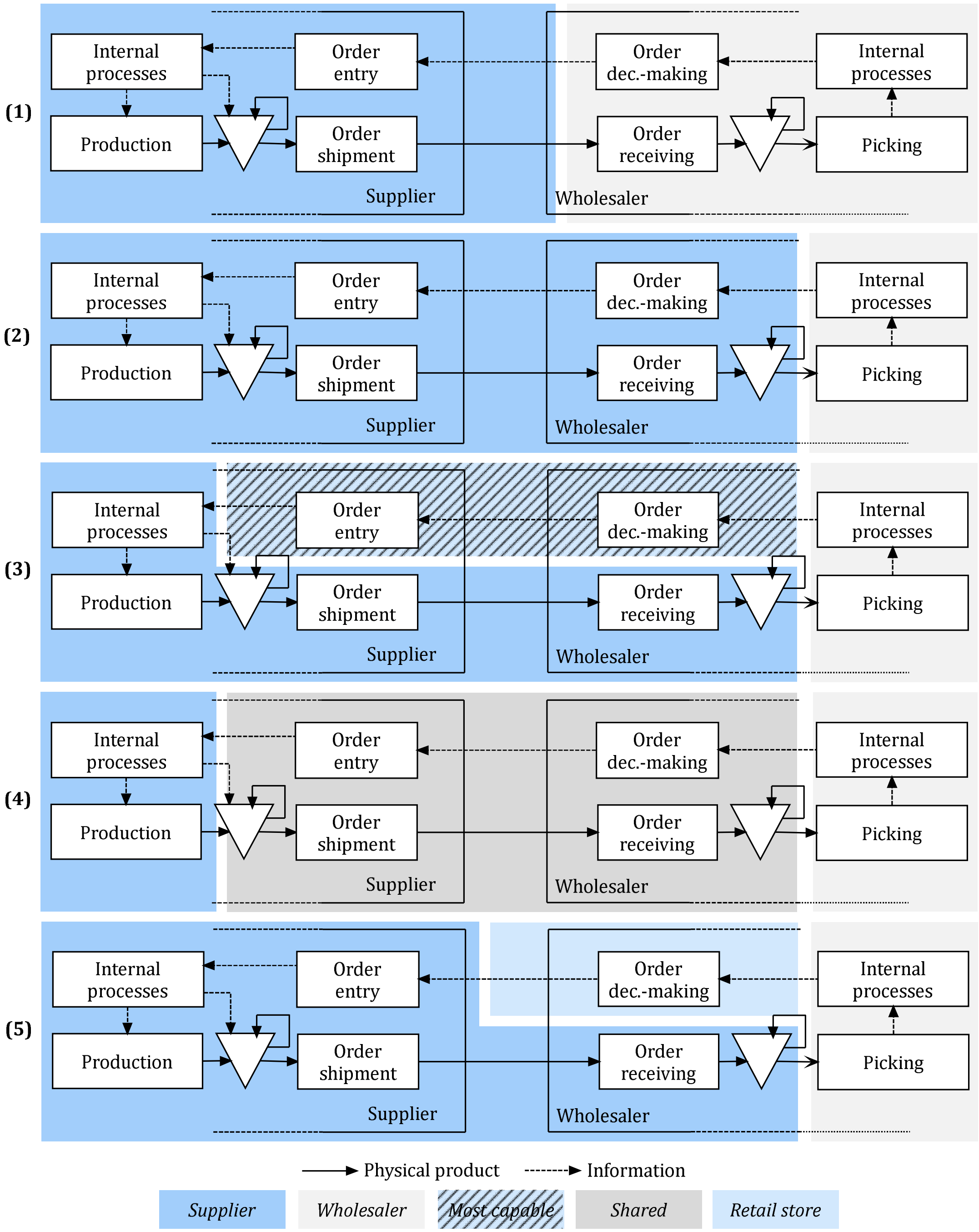
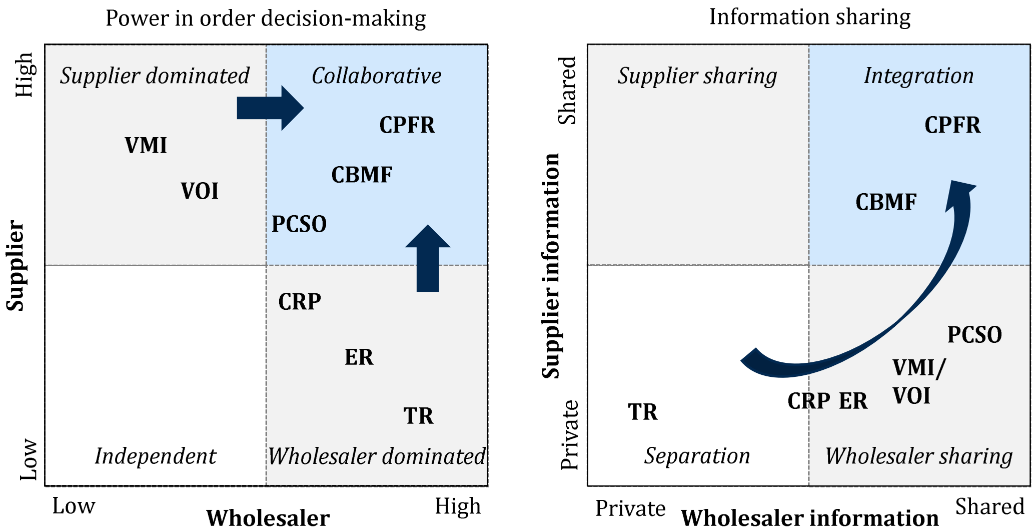


Figure 2-6 summarises the programs adapted from previous comparative studies (Derrouiche et al., 2008; Tyan and Wee, 2003; Verheijen, 2010) and illustrates the different programs in terms of power distribution during order decision-making (i.e. who decides amount and timing of orders) and who shares information during RP&C, in the context of RP&C at wholesaler considering suppliers. While TR, ER, CRP, VOI and VMI generally entail order decision-making by either wholesaler or suppliers, PCSO, CBMF and CPFR entail collaborative order decision-making. Considering when the programs were suggested, there has been a tendency of moving towards more and more collaboration, with a subsequent tendency towards increased integration and information sharing.

Figure 2-6. Decision-power in order decision-making and level of information sharing between wholesaler and supplier in the different ARPs



2.2. PLANNING ENVIRONMENT CHARACTERISTICS

As highlighted in the above, both information sharing and order decision-making are impacted by different characteristics. These so-called planning environment characteristics (PECs) set forth certain requirements for the supply chain-wide RP&C (Entrup, 2005; Hübner et al., 2013; Ivert et al., 2015; Romsdal, 2014). The most fundamental characteristic is perishability, as it changes the entire paradigm of RP&C, compared to non-perishable products (Ferguson and Ketzenberg, 2006; Ferguson and Koenigsberg, 2007). Additional PECs include demand and supply seasonality, weather conditions, promotional activities, product introduction, assortment changes and buyer involvement (Alftan et al., 2015; Fredriksson and Liljestrand, 2015; Hübner et al., 2013; Taylor and Fearne, 2009; van Donselaar et al., 2010), long (uncertain) growth periods with inadequate quality and/or yielding/harvesting of products (Christensen et al., 2017a; Ferguson and Koenigsberg, 2007) as well as specialised production/processing processes (Romsdal, 2014).

Different studies have found and discussed different PECs, impacting different planning and control levels. As an example, Olhager and Rudberg (2002) study manufacturing planning and control; Romsdal et al. (2014) study fresh food suppliers' production planning and control; Ivert et al. (2015) study food processors' sales and operations planning; Dreyer et al. (2018) study retail stores' and wholesaler's sales and operations planning; Jonsson and Mattsson (2003) study detailed material planning, capacity planning, scheduling and sequencing; and Alftan et al. (2015) study supply chain planning and exceptions management. The described PECs in the literature may be grouped into different categories: demand, material flow, engineering changes, supply, product, production and (production) planning. Aligned with the focus on information sharing and order decision-making during RP&C from a wholesaler point of view, four categories are considered relevant: product, demand, supply and production. Table 2-4 lists the different PECs found in the literature, while a detailed description of the different PECs can be found in Appendix A.

Aligned with the focus on information sharing and order decision-making during RP&C from a wholesaler point of view, four categories are considered relevant: product, demand, supply and production. Table 2-4 lists the different PECs found in literature, while a detailed description of the different PECs can be found in Appendix A.

Table 2-4. Product, demand, supply and production-related planning environment characteristics in grocery retailing

Type	Planning Environment Characteristics
Demand	volume, type of procurement ordering, demand type, time distributed demand, source of demand, inventory accuracy, demand-stimulating events, availability requirements, demand frequency/lumpiness, customer service elements, ramp-up level and demand uncertainty
Supply	seasonality of supply, supplier-base complexity, multiple brands, capacity constraints, long supply lead-times, supplier service elements, material supply scrap level, type of procurement ordering, lot size, long and/or unreliable supplier lead-times, number of suppliers and supply uncertainty
Product	BOM complexity, product complexity and variety, degree of value added at order entry, proportion of customer specific items, product/item value, perishability and shelf life, product lifecycle (PLC), volume, inter-relationships in demand among products, shortening product lifecycles, heterogeneity, number of SKUs and the rate of change in the product portfolio
Production	batch size, through-put time, number of operations, lead-time, volume flexibility, product mix flexibility, delivery flexibility, production network, complexity, manufacturing strategy, production uncertainty, phase-in/out date, MP method, planning frequency, planning periods and time fences

2.3. INFORMATION SHARING IN REPLENISHMENT PLANNING AND CONTROL

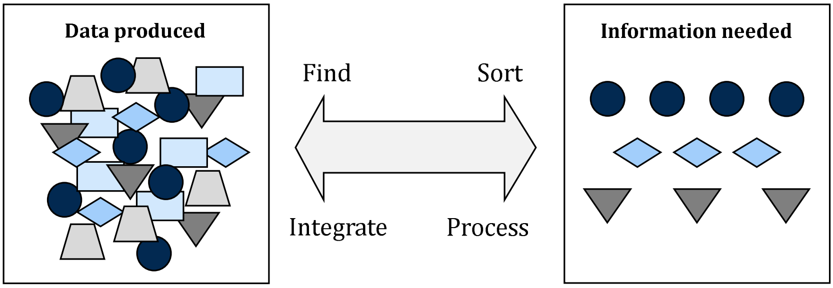
Information sharing is crucial in order for supply chain stages to collaborate and ensure effective decision-making (Aggarwal and Srivastava, 2016; Kache and Seuring, 2014; Lusiantoro et al., 2018), and tends to be a fundamental part of RP&C (Alftan et al., 2015; Choi and Sethi, 2010; Marquès et al., 2010; Pramatari and Miliotis, 2008; VICS, 2004). It is the "inter-organizational sharing of data, information and/or knowledge in supply chains" (Kembro and Näslund, 2014, p. 181). It is about sharing the *right* information with the *right* parties, at the *right* time, at the *right* frequency, in the *right* way, under the *right* circumstances. FFPs benefit more from a high level of information sharing than products with long shelf life (Lusiantoro et al., 2018).

> **Information sharing:** "the capturing and dissemination of timely and relevant information for decision makers to plan and control supply chain operations."
>
> (Simatupang and Sridharan, 2005a, p. 46)

Information sharing improves supply chain performance and responsiveness as well as products' freshness (Cui et al., 2015; Ferguson and Ketzenberg, 2006; Thatte et al., 2012). Further, products with short shelf life seem to have a stronger correlation between supply chain performance and level of information sharing than do products with longer shelf life (Lusiantoro et al., 2018). For FFPs, frequent and timely information sharing should enhance both the supply chain performance (Lusiantoro et al., 2018; Siddh et al., 2015) and the information quality (Gustavsson and Jonsson, 2008). However, merely increasing information sharing may not necessarily result in any positive impact on performance, since sharing irrelevant/too much information may in fact decrease performance and "result in an expected loss" (Choi et al., 2013, p. 136). Ineffective information sharing may trigger "too little" or "too late" mechanisms in the supply chain resulting in lower performance (see Xu, Dong, and Xia (2015)). Moreover, while sharing too little information obviously limits the ability for effective decision-making, sharing too much information may lead to exploitation by the information recipient (i.e. the recipient uses the information against the sender).

In addition, the literature reports challenges regarding the overload of information in business organisations, a situation that has been reinforced in the past years due to e.g. technological advancements and increased data capturing (Edmunds and Morris, 2000). Information overload has different definitions but may generally refer to "having more relevant information than one can assimilate" or "being burdened with a large supply of unsolicited information, some of which may be relevant" (Edmunds and Morris, 2000, p. 18). Endsley (2000, p. 1) points out that today "many operators may be even less informed than ever before" during decision-making, since "there is a huge gap between the tons of data being produced and disseminated and people's ability to find the bits that are needed and process them together with the other bits to arrive". Königer and Janowitz (1995) point out that information is only valuable when structured and cleansed from irrelevancy. Thus, the aim of information sharing during RP&C is to find and sort the needed information amongst all the data produced to ensure that the information is utilised, i.e. "incorporated and actually used in the information receiver's planning processes" (Jonsson and Myrelid, 2016, p. 1769). This entails a systematic approach for closing the information gap and ensuring effective information sharing (Endsley, 2000), as illustrated in Figure 2-7.

Figure 2-7. The information gap (Endsley, 2000)



2.3.1. TAXONOMY OF INFORMATION SHARING

To obtain a better understanding of what the facets of information sharing are, Table 2-5 from Paper #2 summarises the literature and provides a taxonomy of information sharing. It identifies the facets and the research design in which they are discussed. The research design of each study is depicted according to whether it is theoretical, empirical, a simulation or a review; whether the supply chain stages are included; the supply chain structure; the type of information flow; and the product context. The discussed facets are marked by "x". For a detailed description, see Paper #2. Six facets of information sharing were considered: frequency, timing, direction, modality, content and dynamism as well as quality. Table 2-6 depicts the main question answered by each facet.

Table 2-5. Facets of information sharing in the literature (Christensen et al., 2020b)

Author	Research design					Information sharing facets						
	Focus of design	Stages included	Structure studied	Information flow	Context in focus	Frequency	Timing	Direction	Modality	Content	Dynamism	Total
Alftan et al. (2015)	TE	SWR	T	S	G			x	x	x		3
Barratt and Oke (2007)	E	SWR	D	S	(G)R				x	x		2
Cai, Jun and Yang (2010)	E	S	I	U	A				x	x		2
Cao and Zhang (2011)	E	S	I	U	A	x				x		2
Carr and Kaynak (2007)	E	S	I	U	O			x	x	x		3
Chen et al. (2014)	E	S	I	U	O		x	x		x		3
Christensen et al. (2017a)	T	SW	U	U	GFRP		x					1
Christensen et al. (2019b)	T	SWR	T	S	GFRP		x					1
Dimitriadis and Koh (2005)	E	S	I	U	A				x	x		2
Ding et al. (2014)	E	S	I	U	GFP	x		x	x	x		4
Dreyer et al. (2018)	E	WR	I	U	GFP				x	x		2
Fawcett et al. (2007)	E	SRA	I	U	A				x			1
Ha et al. (2011)	TE	S	I	U	A	x			x			2
Huang et al. (2003)	R	A	A	U	A	x	x	x	x	x		5
Hung et al. (2011)	E	S(R)	I	U	A				x	x		2
Ivert et al. (2015)	E	S	I	U	GFP	x			x	x		3
Jonsson and Mattsson (2013)	S	SRC	T	C	A	x			x	x	x	4
Jonsson and Myrelid (2016)	ER	SA	I	U	O	x		x	x	x		4

Author	Research design					Information sharing facets						Total
	Focus of design	Stages included	Structure studied	Information flow	Context in focus	Frequency	Timing	Direction	Modality	Content	Dynamism	
Kaipia et al. (2017)	E	SR	D	S	G	x	x	x		x	x	5
Kehoe and Boughton (2001)	T	S	U	U	A		x		x	x		3
Klein and Rai (2009)	E	SWR	D	S	(R)A			x	x	x		3
Kembro et al. (2014)	R	A	A	A	A			x	x	x		3
Kembro and Näslund (2014)	R	A	A	A	A	x		x	x	x		4
Kembro and Selviaridis (2015)	E	SR	D	CD	G					x		1
Kiil et al. (2019)	E	SWR	D	S	GFRP	x	x	x	x	x		5
Lee and Ha (2018)	(T)E	S	I	U	A	x		x	x	x	x	5
Li et al. (2014)	(T)E	S	I	U	A				x	x		2
Lusiantoro et al. (2018)	R	A	U	U	GFP	x	x		x	x		4
Moberg et al. (2002)	E	S	I	U	A				x	x		2
Mohr and Nevin (1990)	T	A	U	U	A	x		x	x	x		4
Montoya-Torress and Ortiz-Vargas (2014)	R	A	A	U	A					x		2
Myrelid and Jonsson (2019)	E	SA	D	CD	O	x		x	x	x		4
Nakandala et al. (2017)	R	SWRC	E	S/U	GFP	x	x	x	x	x		5
Paulraj et al. (2008)	E	A	I	S	A	x	x		x	x	x	5
Pålsson and Johansson (2009)	E	S	I	U	(F)O	x		x				2
Shey et al. (2006)	E	SR	D	S	O	x		x	x	x		4
Simatupang and Sridharan (2005a)	(T)E	SR	D	U	A		x	x		x		3
Simatupang and Sridharan (2005b)	T	SA	U	U	A		x	x		x		3
Tan et al. (2010)	TE	S	I	U	A			x	x			2

Author	Research design					Information sharing facets						
	Focus of design	Stages included	Structure studied	Information flow	Context in focus	Frequency	Timing	Direction	Modality	Content	Dynamism	Total
Vanpoucke et al. (2009)	E	S(B)	D	S	(G)PO		x	x	x	x		4
Watabaji et al. (2016)	E	SW	D	U	A	x			x	x		3
Xu et al. (2015)	T	SR	D	S	A		x			x		2
Yigitbasioglu (2010)	E	SWR	I	U	A	x		x		x	x	4
Yu et al. (2013)	E	S	I	U	A			x	x	x		3
Zhou and Benton (2007)	E	S	I	U	A				x	x	x	3
Total facets						**18**	**12**	**22**	**31**	**37**	**6**	**126**

Note: Focus of design: E = empirical (incl. case study and surveys), T = theoretical, S = simulation, R = review.
Stages included: S = supplier, W = wholesaler (incl. traders), R = retailer, C = customer, A = anonymous buying/supplying party.
Structure studied: I = individual, D = dyadic, T = triadic, E = extended, A = all, U = undefined/generic.
Information flow: S = serial, C = convergent, D = divergent, U = undefined/generic.
Context in focus: G = grocery, F = food, P = perishable, R = retailing, O = other, A = anonymous/general.
For all: () = partly in focus.

Table 2-6. Overview of included information sharing facets

Facets	Main question answered
Frequency	How often to share the information
Timing	When to share the information
Direction	With whom to share the information
Modality	How to share the information
Content	What information to share
Dynamism	When to share information during product/ demand/supply/technology changes

Studies predominantly focus on information sharing in individual (i.e. single stage) (21) or dyadic (11) relationships, with only four out of 45 studies including three or more supply chain stages (Alftan et al., 2015; Christensen et al., 2019b; Jonsson and Mattsson, 2013; Nakandala et al., 2017). The product/industry context is predominantly unspecified (25), with only eight studies specifically including grocery, perishable and FFP contexts. During the past four to five years, there has been an increase in studies focusing on grocery/perishable/food contexts as well as a general shift towards context-specific research. The articles cover information sharing in terms of sales and operations planning at processor level (Dreyer et al., 2018; Ivert et al., 2015), forecasting quality in relation to animal lifetime aggregated at animal type level (Christensen et al., 2017a), generic fresh food contexts (Lusiantoro et al., 2018; Nakandala et al., 2017), information utilisation during planning (Kiil et al., 2019) and impact of information quality on product quality (Ding et al., 2014). Almost all studies include content and modality, while dynamism is less often included. Moreover, while empirical and review studies tend to cover the most facets, theoretical studies include only a few.

2.3.2. INFORMATION SHARING IN PROGRAMS

Referring to the programs for RP&C, ER entails information sharing about campaigns and promotions (since it is part of Efficient Consumer Response), point-of-sales (POS) data and inventory levels through Electronic Data Interchange (EDI). This allows suppliers to better forecast future demand and prepare for future orders from wholesaler (for internal use), since it reflects actual sales rather than historical orders. In turn, this ensures rapid and efficient replenishment across the supply chain while meeting downstream demand at required service levels (Reyes and Bhutta, 2005). In this way, ER overcomes TR by replacing the physical inventory with information and sharing orders electronically (Kurt Salmon Associates, 1993). The information sharing in CR is similar to ER, with the exception of campaign and promotions information.

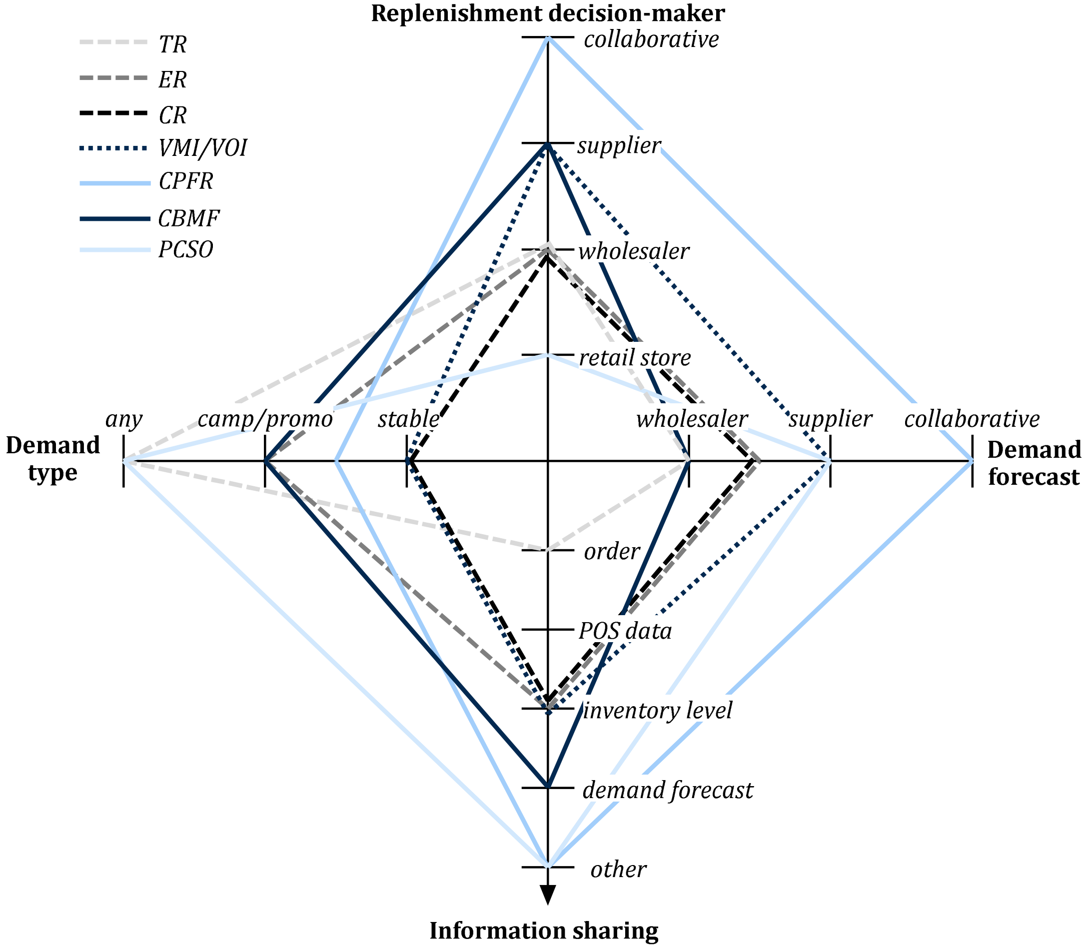
The information sharing and order decision-making during VMI/VOI depends on the advancement and trust between parties, but most often and in its basic form it includes historical orders, POS data and inventory level/allocations, with some studies reporting sharing of demand forecast, delivery schedules, promotions, stock withdrawals, production schedules and incoming orders (De Toni and Zamolo, 2005; Småros et al., 2003; van Hoek and Harrison, 2008; Vigtil, 2007). The information may be accessed by either visual inspection (e.g. "carsale"), batch transactions from wholesaler's ERP systems or on-line access to wholesaler's ERP systems, and is primarily done through EDI or the internet (occasionally phone, email and fax) (Ståhl Elvander et al., 2007; Vigtil, 2007). The supplier may be in charge of both timing and sizing of order replenishment, or one of the two, or propose orders to be confirmed by the wholesaler – and in one variation, the wholesaler may even provide order proposals about when and how much to replenish (Ståhl Elvander et al., 2007). VMI is suitable for high volume products requiring frequent replenishment with stable demand rather than campaigns or high demand variability (Alftan et al., 2015; Barratt, 2003; Sari, 2008).

The information sharing and order decision-making during CPFR is the most extensive and depends on how advanced the CPFR relationship is (Panahifar et al., 2015; Whipple and Russell, 2007). Information shared includes e.g. POS data, inventory levels, promotions, upcoming campaigns, delivery schedules, market-product intelligence, historical demand patters and long terms goals and plans (Alftan et al., 2015). Specifically related to promotion and campaign information, the CPFR utilises this together with manufacturing constraints and raw material availability to resolve exceptions (Stank et al., 1999). The information may be shared through fax, email, phone or advanced internet-based solutions (Hollmann et al., 2015). Although CPFR does not entail that suppliers must share information as such, the collaborative planning allows an improved overview of both demand and supply in the supply chain. However, despite this, it "does not solve all the challenges of grocery replenishment management as a result of the extensive human and financial resource commitment needed" (Alftan et al., 2015, p. 238). CPFR is thus only suggested for suppliers delivering strategically important products (Småros et al., 2003; Whipple and Russell, 2007) with more unstable demand than VMI (Sari, 2008), and it utilises the POS data poorly in terms of demand fluctuations from campaigns/promotions (Barratt and Oliveira, 2001). Information sharing during the retail store version, PCSO, includes products sold since last replenishment, inventory levels, in-store promotions, campaigns, delivery schedules, market-product intelligence, historical demand patters, last sales date, last order date, average weekly sales and back-orders (Pramatari and Miliotis, 2008).

Information sharing during CBMF includes retail stores sharing POS data, inventory levels, orders and information about local campaigns and situations, and suppliers sharing information about their operations. With wholesaler in charge of forecasting and suppliers in charge of replenishment decisions, CBMF splits the order decision-making process.

Figure 2-8 provides a cartographic representation of the programs in terms of replenishment and forecasting responsibility as well as the (minimum) information shared and which products the programs are appropriate for. The programs predominantly share orders, POS data and inventory levels, mainly with wholesaler or suppliers as decision-makers for when and how much to order. For the demand forecast, the programs use separated forecasting, with ER and CR entailing information sharing for the purpose of allowing suppliers to anticipate future demand for their own internal use. For both VMI and CPFR, multiple different information was reported to be shared and thus the cartography illustrates the lowest level of information shared. Hence, when sharing e.g. inventory level then POS data and order information is also shared – and when sharing other information then all the above information is also shared.

Figure 2-8. Cartography of RP&C programs



There are limited recommendations as to short-term information sharing and the programs mainly differ in terms of the order decision-making, i.e. who is responsible for sizing and quantifying the replenishment and who is responsible for forecasting the upcoming demand. The information sharing is predominantly described in terms of what information to share (e.g. POS data, inventory level, orders and campaign information) and how it could be shared (e.g. EDI, system integration or using the internet), with empirical studies and reviews often pointing out that in practice there seems to be no consensus and that it depends on e.g. level of trust and engagement to collaboration (Alftan et al., 2015; Hollmann et al., 2015; Panahifar et al., 2015; Pramatari and Papakiriakopoulos, 2002; Ståhl Elvander et al., 2007). Moreover, the inconsistency regarding what the programs govern and their premises seems to result in an even more opaque understanding (Marquès et al., 2010; Ståhl Elvander et al., 2007).

2.3.3. POS-BASED DEMAND INFORMATION SHARING

POS data is considered the most accurate demand signal and a countermeasure to shortages and demand amplification in the supply chain, i.e. the bullwhip effect (Croson and Donohue, 2003; Disney and Towill, 2003b; J.S. et al., 2019; Småros et al., 2003; Vigtil, 2007), and to demand/supply planning nervousness (Kaipia et al., 2006). It is generally encouraged to share as part of essential demand information (Byrne and Heavey, 2006; Disney and Towill, 2003b; Kulp, 2002; Simatupang and Sridharan, 2005a; Vigtil, 2007) and is particularly valuable for perishable products with short shelf life (Ferguson and Ketzenberg, 2006; Lusiantoro et al., 2018). However, studies suggest that e.g. CPFR and collaborative store ordering can utilise POS data better than e.g. VMI. This is due to their higher level of information sharing and focus on promotions/exceptions management (Alftan et al., 2015; Panahifar et al., 2015; Pramatari and Miliotis, 2008). Further, it seems to be more beneficial for a small retailer to share POS data with a supplier than for a large retailer, due to e.g. risk pooling, although it is more likely that a large retailer shares the POS data due to the required investments in information technology for receiving, decoding and understanding the large amounts of POS data (Williams and Waller, 2011). Kaipia et al. (2017, p. 13) point out that if the “customer's share in the supplier's overall volumes is low or if production planning cycles are long, the value of POS sharing may be very small or even non-existent.”

Challenges are reported in relation to understanding the detailed POS data, such as the discrepancy in sales across sales points and that not all supply chain stages may be able to collect, process and transmit POS data (Barratt and Oliveira, 2001; Kaipia and Hartiala, 2006; Williams et al., 2014). Particularly, suppliers often struggle to effectively utilise the bare POS data for predicting orders and improving performance due to the high level of detail in POS data (i.e. granularity) and lacking reflection of downstream behaviour and operations (Narayanan et al., 2019; Raman et al., 2001). POS data is reported to not be precise, since the real-life demand may be higher than registered, as it does not reflect demand from out-of-stock situations where products could have been sold if available (i.e. censored demand). Further, inventory levels may be too high when based on store receipts and POS data, since these do not include the impact of shrinkage, misplacement and/or transaction errors (Chen and Mersereau, 2015). Information on inventory levels is considered complementary to POS data (Jonsson and Mattsson, 2013; Williams et al., 2014), although studies point out that the relative inaccuracy in inventory levels will only add additional errors into the forecasting (Nachtmann et al., 2010; Raman et al., 2001) and (thereby) increase the chance of stock-outs (Gruen et al., 2002). To minimise the impact of these phenomena it has been proposed to include an (estimated) inaccuracy factor when planning demand (Chen and Mersereau, 2015), and/or use inverse POS data (i.e. periods with no sale) to detect the out-of-stock situations and thus to react faster (Corsten and Gruen, 2003; Fisher and Raman, 2010). Moreover, POS data does not reflect that retail stores may e.g. intentionally order too much to buffer against uncertainties or too little to use stored amounts, and/or adjust ordered quantities to account for e.g. product cannibalisation/substitution. Thus, merely receiving POS data without any additional information may lead the receiving party to draw incorrect conclusions about future demand, thereby resulting in ineffective decision-making about internal production (Kembro and Selviaridis, 2015). POS data must be complemented with (demand) information from other sources as well (Jonsson and Mattsson, 2013; Williams and Waller, 2011).

Appendix B summarises and provides a selected overview of recent empirical studies on the use of POS data, focusing on grocery retailing and food products, from a wholesaler and retail store point of view. For a detailed discussion of the value of sharing and using POS data in inventory order decision-making and forecasting, see Paper #9.

The literature reports different results without any clear recommendation(s), and only a few studies include three or more supply chain stages. Some research indicates a low value of POS data sharing when retailers' inventory levels are high, since there is then no need for ordering products, and high when getting close to the order-triggering point – although POS data may then be redundant since the retailer will send an order anyways (Cachon and Fisher, 2000). And further, when suppliers manage the inventory control (e.g. VMI, CBMF), POS data adds value by reducing the impact of order-batching, demand uncertainty and low supplier responsiveness in a make-to-order environment (Småros et al., 2003; Vigtil, 2007). Other literature suggests that the value of POS data depends on the underlying demand process and replenishment lead-time, and that lower inventory levels and average costs may be obtained when demand is highly correlated over time or characterised by high variance, or when replenishment lead-times are long and/or more echelons are included (i.e. broadening supply chain scope) (Jonsson and Mattsson, 2013; Lee et al., 2000).

No identified study empirically explores the effect of sharing real-time POS-based information for FFPs at different time-points during RP&C i.e. demand forecasting and inventory control combined into one process. Also, no study focuses on when it is valuable to share real-time POS-based information over order-based, considering the demand type and processing method at a product-level.

2.4. ORDER DECISION-MAKING IN REPLENISHMENT PLANNING AND CONTROL

While the one side of RP&C is information sharing, the other is order decision-making, where the central focus is on when and how much to replenish. Following Fisher and Raman (2010), the wholesaler/retailer has three tactics available to balance demand and supply in retailing, namely forecasting accuracy, supply flexibility and inventory building – which must be applied in the listed order. Forecasting accuracy entails a cost-efficient supply chain (i.e. reduced waste and increased availability). However, forecasting is always wrong (Hanke and Wichern, 2009). Thus, the accuracy of the forecast is platform for further decision-making during RP&C. Supplier flexibility is important when selecting the most accurate forecasting model. Since forecasting is never completely correct, being able to respond quickly upstream is required. Not being able to respond to demand leads to excessive costs, influencing supply chain profit (Hübner et al., 2013). Since inventory building is "the most expensive tactic of the three, [it] should be used only after you've pushed accurate forecasting and supply flexibility to their limits" (Fisher and Raman, 2010, p. 128). Stank et al. (1999, p. 76) also point out that "holding high levels of anticipatory inventory may offer a way to avoid out-of-stocks, but it is a very expensive method of avoidance."

For FFPs, shelf life and perishability must be considered so as to ensure an effective reduction of out-of-stock and increase in freshness (Broekmeulen and van Donselaar, 2017; Eriksson et al., 2014). This places high requirements on the order decision-making during RP&C, i.e. inventory control. The higher inventory levels, the greater the risk of waste due to the reduction in shelf life, and the lower inventory levels, the higher risk of unavailability. As FFPs experience growing importance in the general grocery market with increasing consumer requirements (Nielsen, 2018, 2017), this only emphasises the need for ensuring particularly effective decision-making regarding when and how much to replenish.

The following first addresses forecasting accuracy and then order decision-making in relation to when and how much (i.e. RP&C), with a focus on current methods for replenishing perishable products.

2.4.1. EVALUATING DEMAND FORECASTING

Demand forecasting is a key remedy in inventory control of FFPs in uncertain environments, and its accuracy impacts the effectiveness of planning and subsequent levels of waste and quality (Adebanjo, 2009; Petropoulos et al., 2018; Teller et al., 2018). Inaccuracy in forecasting can lead to high costs in the FFP supply chain (Kourentzes et al., 2020). Not being able to predict future sales accurately may lead to out-of-stock situations (Aastrup and Kotzab, 2010; Corsten and Gruen, 2003; Gruen et al., 2002) or reduction of product freshness (potentially causing waste) (Broekmeulen and van Donselaar, 2017; de Moraes et al., 2020; Mena et al., 2014). Since wholesaler balances supply with demand, this bridges the industry with the retailing. Therefore, wholesaler must be able to effectively and efficiently interpret the accuracy of the forecasts and plan accordingly (Kuhn and Sternbeck, 2013), to reduce the negative impact of the bull-whip effect upstream (Chen et al., 2000). Accuracy is measured through the magnitude of deviations between actual and forecasted demand.

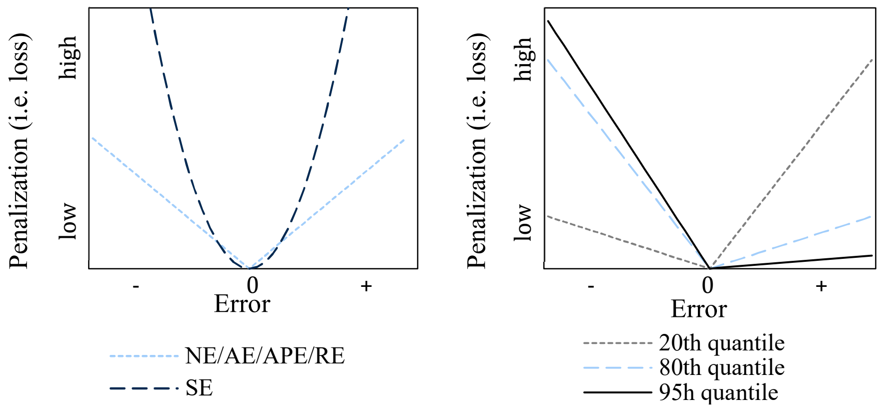
Striving for effective evaluation, grouping products according to their (forecasted) demand and other parameters (van Kampen et al., 2012) usually supplies the basis for deciding when and how much to replenish. In this manner, the selected forecasting model has an impact on product availability and freshness qua the derived replenishment approach. In practice, a set of different accuracy measures are usually used to effectively and consistently evaluate and select the most accurate model. Although this may seem straightforward in terms of automatically selecting models (i.e. efficiency), studies point out a general lack of trust in automated algorithm-based selection of forecasting models (Alvarado-Valencia et al., 2017). Further, while one forecasting model may have high accuracy according to one measure, it may have low accuracy according to another (Kolassa, 2020). Moreover, research has shown that human and qualitative evaluation can outperform automatic selection based on algorithms (Petropoulos et al., 2018). Despite this, it is impossible for a wholesaler to manually evaluate the forecasting model of every product in their portfolio. A wholesaler product portfolio may contain up to hundreds of thousands of products. Hence, there is a need for ensuring that forecasting accuracy is evaluated according to the FFPs' characteristics.

Numerous different accuracy measures exist, based on statistical evaluation of historical demand (Hanke and Wichern, 2009; Hyndman, 2006; Hyndman and Koehler, 2006; Kolassa, 2016; Mehdiyev et al., 2016). Some measures also suit products with demand intermittency (Kolassa and Schütz, 2007). In the grocery retailing context, accuracy measures such as Mean Forecast Error (MFE; also used as tracking measure), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) (see e.g. Huber et al., 2017; Priyadarshi et al., 2019; Van Donselaar et al., 2016). In this PhD research study, the focus is on six of the most known evaluation techniques (i.e. penalisations). Table 2-7 lists the different ways of penalising the deviations, with $P(\hat{y}_t, y_t)$ as the mathematically expressed evaluation of the deviations between forecasted demand $\hat{y}_t$ and actual demand, y_t. Figure 2-9 illustrates how the magnitude of penalisation increase as the magnitude of deviation increases, i.e. larger/smaller forecast errors. For a more detailed discussion of the different accuracy measures, see Paper #6.

Table 2-7. Common penalisations in forecasting accuracy measures (Christensen et al., 2020a)

Symmetry	**Penalisation, $P(\hat{y}_t, y_t)$**	**Valuation type**
Symmetry	$(\hat{y}_t - y_t)$	*normal error (NE)*
	$\lvert\hat{y}_t - y_t\rvert$	*absolute error (AE)*
	$(\hat{y}_t - y_t)^2$	*squared error (SE)*
	$\lvert(\hat{y}_t - y_t)/y_t\rvert$	*absolute percentage error (APE)*
	$\lvert(\hat{y}_t - y_t)/\hat{y}_t\rvert$	*relative error (RE)*
Asymmetry	$\begin{cases} \alpha \cdot \lvert\hat{y}_t - y_t\rvert & ,if \quad \hat{y}_t \leq y_t \\ (1-\alpha) \cdot \lvert\hat{y}_t - y_t\rvert & ,if \quad \hat{y}_t > y_t \end{cases}$ $where\ \alpha \leq 1$	*asymmetrical absolute error*

Figure 2-9. Penalisation symmetry for different accuracy measures (Christensen et al., 2020a)



A challenge of current accuracy measures is their symmetrical penalisation, regardless of whether deviations are positive or negative, large or small – the consideration of loss is the same (Hyndman, 2006; Hyndman and Koehler, 2006; Kolassa, 2016; Kolassa and Schütz, 2007). For FFPs, there is a discrepancy in the loss, i.e. the impact from a deviation depends on whether it is positive/negative or large/small. While under-forecasting (i.e. negative deviation) entails lower fill-rates with higher out-of-stock, over-forecasting (i.e. positive deviation) entails higher fill-rates but with a higher risk of waste.

Considering this discrepancy, asymmetrical absolute error, also known as quantile loss function, allows a differentiated penalisation depending on whether the deviation is positive or negative (Granger, 1999; Granger and Pesaran, 2000; Lee, 2007). It assumes that under-forecasting (i.e. out-of-stock) is more critical than over-forecasting (i.e. inventory building) (Kourentzes et al., 2020; Trapero et al., 2019). However, this is not always true. Since some FFPs can only be stored for a very short time before expiration, under-forecasting does not always result in a greater loss, and the structure of costs is also more complex when trying to reduce the amount of waste while satisfying consumer requirements (Buisman et al., 2019; Chen et al., 2019; He et al., 2018). Instead, the impact of the deviation depends on the given FFP's shelf life and the demand in the following days (before expiration). As an example of over-forecasting, when the excessive FFPs can be kept in inventory and absorbed (i.e. sold) through the following days' demand – before they expire or induce a lower close-to-expiration price – the impact is small. When the FFPs cannot be absorbed, the impact is higher, since the FFPs turn into waste. Consequently, for FFPs with very short shelf life, over-forecasting may have an immediate impact, since it is not possible to keep products in inventory unless reducing sales-price. It is therefore relevant to investigate how forecasting models can be evaluated considering the inventory of FFPs to accurately assess their impact.

2.4.2. INVENTORY CONTROL

The second aspect of order decision-making is inventory control. Multiple models and policies exist for perishable products with fixed (deterministic) or random (probabilistic) shelf life, fixed or continuous review period and deterministic or stochastic demand modelling (Bakker et al., 2012; Goyal and Giri, 2001; Raafat, 1991; Silver et al., 1998; Steven Nahmias, 1982). When shelf life is one day, the newsboy problem is relevant (Silver et al., 1998), and when it is two days a variation of the newsboy problems has been proposed for stochastic demand (Nahmias and Pierskalla, 1973). When shelf life is up to a few weeks, there are a minimum of four different policies: the old inventory ratio (OIR) policy (Duan and Liao, 2013), the age-and-stock-based (CASB) policy (Lowalekar and Ravichandran, 2017), the basic EWA policy (Broekmeulen and van Donselaar, 2009) and the adjusted EWA_{SS} policy (Kiil et al., 2018b). Since FFPs may have several days shelf life, e.g. cold cuts, fresh meat and dairy products, the OIR, CASB and EWA policies are considered.

The two-step OIR policy minimises the number of outdated products given a predetermined limit for out-of-stock. It follows an order-up-to approach and places an order if the ratio between outdated and total inventory position on hand is larger than specified. The order size corresponds to the number of outdated products. Simulations of blood products show a reduction from 19.6% to 1.04% of outdated products while ensuring a high fill-rate (Duan and Liao, 2013).

The CASB policy is a variation of OIR with a continuous review (Lowalekar and Ravichandran, 2017). It follows a re-order point approach and places an order when the inventory position drops to a certain level or when the oldest batch has aged *t* units of time; whichever occurs first (Lowalekar and Ravichandran, 2017). Since review is continuous a lower safety stock is required (Silver et al., 1998).

The EWA policy considers the number of outdated products within a review period and shows results of an increase of inventory availability of 17.7% and waste reduction of 3.4% for perishable products with 4–7 days shelf life, when compared to a stock-based policy. To reflect the practice in grocery retailing, EWA batches the store orders according to case sizes (Broekmeulen and van Donselaar, 2009).

One version of EWA, EWA_{SS} (Kiil et al., 2018b), considers the size of safety stock relative to the number of outdated products within a review period. It has shown 10.3% increase in inventory availability and 10.7% waste reduction in a simulation study of FFPs, when compared against a stock-based policy. The latest EWA_{SS} suggested by (Kiil et al., 2018b) is provided in Equations (1) and (2):

EWA_{SS} heuristic (Kiil et al., 2018b)

If

$$I_t - \sum_{i=t+1}^{t+R+L-1} \hat{O}_i < \sum_{i=t+1}^{t+R+L} E[D] + SS \tag{1}$$

then

$$Q_t = \begin{cases} \max\left(\dfrac{\sum_{i=t+1}^{t+R+L} E[D] + \sum_{i=t+1}^{t+R+L-1} \hat{O}_i - I_t}{B}, 0\right) & \text{if, } SS < \displaystyle\sum_{i=t+1}^{t+R+L-1} \hat{O}_i \\ \max\left(\dfrac{\sum_{i=t+1}^{t+R+L} E[D] + SS - I_t}{B}, 0\right) & \text{if, } SS \geq \displaystyle\sum_{i=t+1}^{t+R+L-1} \hat{O}_i \end{cases} \tag{2}$$

$E[D]$ = expected product demand within review time
I_t = inventory position of product at time t
$\hat{O}_i$ = estimated number of products to expire within review time
SS = safety stock for product

Although EWA_{SS} includes the size of safety stock relative to the estimated number of products that will outdate, it is for only a single product, much like EWA, OIR and CASB. Since they include only one product, they do not consider the additional demand created from other products which are sold out and out-of-stock (i.e. substitutions demand). Further, they do not include the impact of selling products close to expiration at a reduced price.

2.5. PERFORMANCE EVALUATION OF REPLENISHMENT PLANNING AND CONTROL

To adequately report on changes, and effectively draw conclusions from the evaluation and discussion of research findings, essential performance measures are needed. Further, to reflect reality, the measures should be relevant to the grocery/retailing industry and particularly consumer requirements. From the literature and different case studies throughout the PhD research studies, the following outlines the applied performance evaluation measures for RP&C of FFPs. In total, four primary performance measures are used in this PhD research study. Table 2-8 lists the consumer requirements together with which measure is used in this study to reflect these requirements, as well as a description of what the measure reflects.

Table 2-8. Performance measures used in this PhD study

Consumer requirements	Measure	Description
Availability	Fill-rate	The delivered number of products out of total ordered, expressed as percentage
Freshness	Inventory days	The average number of days a product is stored before sold
	Inventory level	The average number of products stored per day
Waste	Expired products	The number of products exceeding shelf life
Costs	Costs	Monetary value (only used in selective analyses)

Starting with availability, this is the most fundamental measure. It represents whether a product is available for purchase or not. Consumers are relentless and/or cause demand noise if they cannot find their desired product, by either switching store or purchasing another product (BlueYonder, 2017; Gruen et al., 2002; RELEX, 2020). Availability is thus also a favoured measure in the literature when evaluating findings and performance. Availability may be calculated in at least three different ways, aside from being percentwise or numerical[1], namely loss rate, fill-rate and service level (Huber et al., 2017). It reflects the percentwise amount of products delivered out of ordered, as in Equation 3.

Given that FFPs are perishable and have only limited days shelf life and that consumers have high requirements as to FFPs' freshness, this study uses both the average number of days FFPs are in inventory and the average number of FFPs in inventory per day. Considering the ongoing degradation of FFPs, increasing remaining shelf life in stores with one day results in improved freshness, availability and waste-levels (Broekmeulen and van Donselaar, 2017).

[1] Loss rate (amount of products to discard/waste in relation to actual sales), fill-rate (percentage of actual demand that can be met) and service level (the probability that actual demand can be met on any given day).

The inventory days (ID) and average inventory level (AIL) are described by Equations 4 and 5.

Another very often used measure to evaluate performance in the perishable supply chain is waste. As highlighted above, waste has a double climatic impact and is gaining increasing attention on national and international climate agendas. Moreover, waste is used for measuring different planning and control activities such as RP&C (de Moraes et al., 2020; Hvolby and Steger-Jensen, 2015; Kiil et al., 2018b; Mena et al., 2014, 2011, 2009). Waste (W) is described by Equation 6.

Finally, costs are used to measure the direct impact on the profit base (Hübner et al., 2013). Costs (C) covers availability (costs from sold out), freshness (lost profit due to price reduction) and waste (total handling costs of expired products), as in Equation 7.

Performance measures

$$\mathrm{FR_p} = \begin{cases} 100 & , \quad \text{if } 0 < \mathrm{Q_{ordered,t,p}} = \mathrm{Q_{delivered,t,p}} \\ \frac{1}{n}\sum_{t=1}^{n} \frac{\mathrm{Q_{delivered,t,p}}}{\mathrm{Q_{ordered,t,p}}} * 100 & , \quad \text{if } 0 < \mathrm{Q_{delivered,t,p}} < \mathrm{Q_{ordered,t,p}} \end{cases} \tag{3}$$

$$\mathrm{ID_p} = \frac{\sum \mathrm{Q_{delivered,p}}}{\mathrm{AIL_p}} \tag{4}$$

$$\mathrm{AIL_p} = \frac{1}{n}\sum_{t=1}^{n}\left(\max\left(\mathrm{I_{beginning,t,p}}, \mathrm{OUL_{t,p}}\right) - \mathrm{Q_{store,t,p}}\right) \tag{5}$$

$$\mathrm{W_p} = \sum_{t=\mathrm{OUL_t} > \sum_{T=t}^{T+S} \hat{y}_{t,p}}^{n} \left(\mathrm{OUL_{t,p}} - \sum_{T=t}^{T+S} \hat{y}_{t,p}\right) \tag{6}$$

$$\mathrm{C_p} = \mathrm{C_{sold\ out}} + \mathrm{C_{waste}} \tag{7}$$

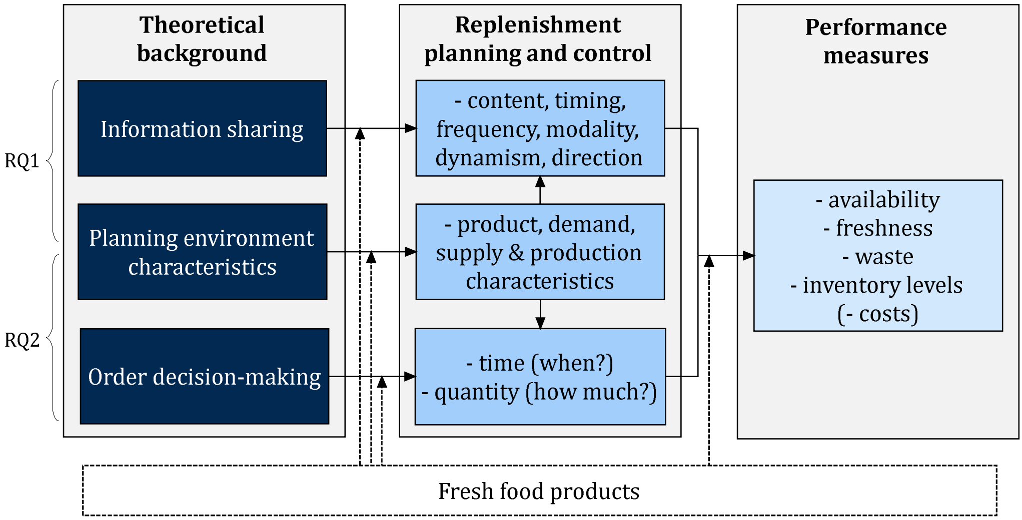
$Q_{delivered,t,p}$ = quantity delivered for product *p* at time *t*
$Q_{ordered,t,p}$= quantity ordered for product *p* at time *t*
$Q_{store,t,p}$ = quantity ordered from retail stores for product *p* at time *t*
$I_{beginning,t,p}$ = inventory level for product *p* at beginning of time *t*
OUL_t = order-up-to level
$\hat{y}_{t,p}$ = forecasted demand for product *p* at time *t*
S = shelf life in time periods *t*

2.6. RESEARCH SUBJECT FRAMEWORK

Based on the previous sections, this section summarises the theoretical background in relation to the research objective and research questions.

The objective of this research study is to contribute to how PECs impact effective RP&C, i.e. order decision-making and information sharing for FFPs. Effectiveness relates to high availability and freshness with low waste and inventory. With the two main research questions posed, the objective separates into information sharing and order decision-making – both concerning PECs. Figure 2-10 depicts their relationship.

Figure 2-10. Research subject framework



3

RESEARCH DESIGN

Central to this study is the creation of theoretical knowledge advancing the understanding of how planning environment characteristics (PECs) may be reflected in the design of effective order decision-making and information sharing during replenishment planning and control (RP&C), while simultaneously advancing industrial practice. This entails collaboration with empirical cases, and thus this research study consists of nine different sub-studies, reflecting wholesaler, retail stores and/or FFP processors. The use of empirical cases has enhanced the research study by providing access to empirical information and data about supply chain stages, in turn ensuring a holistic overview and understanding.

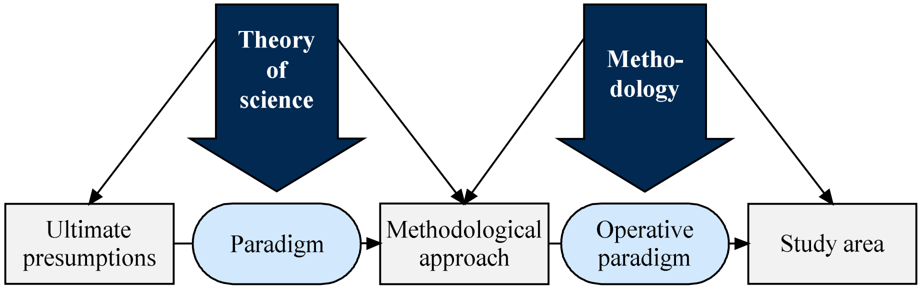
The following four sections summarise and relate the different research sub-studies to the overall PhD research project and research design. For a detailed description of the methodologies used in the sub-studies, please see appended Papers 1–9. Section 3.1 introduces the research design framework applied in this PhD research study. Section 3.2 presents the philosophical point of view and clarifies the presumptions and research paradigm of this research study, namely, critical realism. It further presents the methodological approach, where special attention is given to the systems modelling approach, type of modelling and the different ways of inferring to/from empirical/theoretical stances. Section 3.3 presents the operative paradigm and the specific methodologies applied throughout the sub-studies as well as the research quality. Finally, Section 3.4 provides an outline of the different case participants.

3.1. RESEARCH DESIGN FRAMEWORK

For any scientific project, a carefully selected research design is desirable (Guba and Lincoln, 1994). The research design guides and supports the researcher in following both a systemic and structured research approach that may be subject for repetition by other researchers (Paltridge & Starfield, 2007), and also ensures quality in the collection, analysis and interpretation of data and information. Creswell (2009, p. 3) describes a research design as the “plan and the procedures for research that span the decisions from broad assumptions to detailed methods of data collection and analysis.”

Arbnor and Bjerke's (1997) framework (shown in Figure 3-11) supports the research through five elements related through two fundamental concepts: philosophy of science and methodology.

Figure 3-11. Research design framework by Arbnor and Bjerke (1997)



Philosophy of science relates to the general and fundamental ideas and understanding of the reality of the world in which the research study is carried out. It defines the paradigm and bridges the ultimate presumptions with the methodological approach. According to Arbnor and Bjerke (1997, p. 14), a paradigm consists of "a conception of reality (view of the world), a conception of science, a scientific ideal, and has an ethical/aesthetic aspect." Hence, the paradigm defines the ontological and epistemological stance and also clarifies the consequent de-/limitations of the available methodological approaches to the research study.

Methodology relates to understanding how methods are constructed and how one can investigate and obtain knowledge, mainly grouped into either qualitative models, quantitative models or a mix of the two. The methodology defines the operative paradigm, i.e. the specific methodological procedures and methodics of the study.

3.1.1. PARADIGMATIC STANCE

Several different paradigms exist, all with a different philosophical point of view (Creswell, 2009; Guba and Lincoln, 1994; Okasha, 2002). Each paradigm has different perceptions of the study of being, i.e. what can one know, what is reality and what exists (ontology), as well as the study of knowledge, i.e. how can one know, what is valid and how can one obtain it (epistemology). Dependent on these, the paradigms further differ in how one can go about discovering and creating knowledge about reality (methodology). The spectrum of paradigms ranges from pure positivism to pure (social) constructivism. At the one extreme, a positivistic paradigm entails an objective and independent reality, which the researcher can apprehend directly and where the research aim is to make predictions. Following natural science, the methodology is quantitative and employs mathematics and statistics. At the other extreme is the constructivist paradigm. Constructivists consider reality as a "manifestation of human intentionality" which the researcher cannot apprehend independently and where the research aim is to understand (Arbnor and Bjerke, 1997, p. 44). Its existence and features are not independent of the researcher's cognition of it/them.

The author of this thesis has more than 15 years employment experience at the participating wholesaler, with longer periods in several departments across the value chain, e.g. procurement, purchasing and warehouse. Consequently, much knowledge and information has been obtained by the researcher regarding the different processes related to RP&C, such as ordering, receiving, picking, packing and shipping. This limits the pure objective research (i.e. positivism) where observations will not interfere with the phenomena and inferred results/findings. However, as the (second part of the) research study is solution-oriented with a focus on effectiveness (based on quantitative information), a constructivist paradigm would also not be appropriate.

This PhD research study follows a realist paradigm which is based on a mix of the two extremes, namely critical realism (Bhaskar, 1986; Guba and Lincoln, 1994). From an ontological point of view, critical realism understands reality as objective and independent, stratified across the real world, actual level of events and empirical observation. Critical realism considers reality as partly independent of the researcher's knowledge and theories about it. From an epistemological point of view, critical realism sees the real world and the researcher's cognition of the real world as strictly distinct. The researcher' perception is always historically and contextually based, and it is possible to obtain knowledge about the fundamental parts and objects in the system, and not only the empirically observable elements. Following critical realism, there is an anticipation of cumulative and continuously more certain knowledge, i.e. as the research study progress, more and more (empirical and theoretical) data/information confirms or rejects the ongoing knowledge building.

Critical realism is different from the otherwise extensively followed positivism, according to which everything per se can be observed, described and predicted through both quantitative methods and statistical analyses, assuming full resemblance of the real word (Aastrup and Halldórsson, 2008; Adamides et al., 2012; Mingers, 2004). Considering the supply chain with FFP complexities and human decision-making, critical realism allows one "to see supply chains from many different perspectives and obtain a better picture/knowledge of the related phenomena by applying research methods that belong to different research paradigms" (Adamides et al., 2012, p. 924). Thus, critical realism entails both the constructivist qualitative research methods (e.g. interviews) and the positivist quantitative research methods (e.g. statistical analysis).

3.2. METHODOLOGICAL APPROACH

The methodological approach clarifies how can we go about acquiring that knowledge, and is guided by the paradigmatic stance (Brooks, 2013). According to the research framework (Arbnor and Bjerke, 1997), three overall methodological approaches exist. They are the analytical approach (positivistic), actors approach (constructivist) and systems approach (in between). Confining to critical realism, the systems approach is applied with "reality as mutually dependent fields of information" (Arbnor and Bjerke, 1997, p. 44). System theory's way of embodying systemic and holistic structures complements critical realism (Mingers, 2011).

According to systems theory, a supply chain is an open environment, in which the studied object/phenomena represents a composition of different components in a purposive and structured homeostatic system. Each component automatically reconfigures and calibrates according to external impacts, i.e. by themselves without initiation from an external intervention (Arbnor and Bjerke, 1997; Caddy and Helou, 2007). See the definition of a system below.

> **Definition of a system:** "a composition of finite elements or components; the components combine to form an integrated whole; and the integrated whole exists in order to achieve some purpose."
>
> (Caddy and Helou, 2007, p. 322)

A supply chain may be decomposed into "people, organisations, technological infrastructure, information flows, flows of physical goods, and flows of intangible services" (Caddy and Helou, 2007, p. 322). Each of these components represents a sub-system. The sub-systems are structured together with other sub-systems into one large system, i.e. a super-system. The super-system obtains from the sub-systems in a hierarchical manner, where the higher the super-system, the higher the aggregation; vis-à-vis, the lower the sub-system, the more the disaggregation. Studying RP&C, the focus is mainly on the components of the information flow and product flow in relation to the planning environment characteristics. Although this study recognises the existence of the people, organisation and technological infrastructure, and that certain limitations may derive from these, this is delimited from this study. While information flow relates to the system of sharing information in the supply chain (i.e. with external sub-systems), product flow relates to the order decision-making, i.e. forecast evaluation and inventory control. Each of these sub-systems relates to each other through their properties. As an example, the properties of information sharing (i.e. timing, content, frequency, direction, modality and dynamism) each relate to the properties of order decision-making (timing and quantity). Hence, depending on when information is shared, the order quantity to replenish may vary. In this way, the super-system of RP&C consists of three sub-systems (information sharing, forecasting accuracy and order decision-making), each with different properties, impacted by PECs.

At a general level, as part of the whole (i.e. ontological stance), this PhD research study focuses on two operations: analysis and synthesis. The analysis analyses the properties of the different sub-systems and divides these into components in a structured manner, in order to understand today's whole i.e. as-is (RQ1). The synthesis relates the sub-systems to one another in a structured manner, in order to develop and propose a solution to the problem of tomorrow's whole i.e. to-be (RQ2). When dividing the RP&C into (sub-)sub-systems (information sharing, order decision-making and PECs), it makes the perception and structure of the super-system very complicated. To comprehend this complexity, while reflecting the reality (i.e. epistemological stance in critical realism), creating a model may be useful to ensure a holistic and objective view of the stratified world. However, attention should be maintained on the fact that the model is merely a fraction of the whole (i.e. a sub-system), and thus only provides a delimited view.

3.2.1. QUANTITATIVE AND QUALITATIVE MODELLING

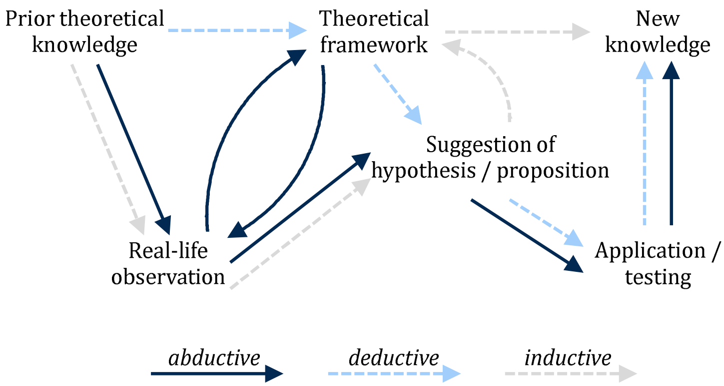
According to Paltridge & Starfield (2007, p. 119) "methods refers to the actual research instruments and materials used. The chosen methodology informs the choice of methods and what counts as data." In critical realism, there is no definitive modelling methodology, but rather a mix of many methods (quantitative and qualitative), depending on the context and subject of the study. However, given the study area, i.e. quantitative decision-making (RP&C) (Hübner et al., 2013), quantitative modelling is predominantly used, with the qualitative approach (i.e. mix-method) used for supporting or clarifying/investigating specifically relevant scenarios and information when needed. The quantitative modelling also supports the performance measuring of RP&C, namely the quantitative change in availability, freshness, waste, inventory level and costs. The complementation between quantitative and qualitative modelling reflects both measuring the measurable (i.e. goal of quantitative research) and understanding the meaningful (i.e. goal of qualitative research) (Brooks, 2013; Creswell, 2009).

Following RQ1 and RQ2, the PhD research study evolves through an analysis and solution phase (i.e. synthesis). The quantitative/qualitative models used in each of these phases may generally be classified according to three groups. First, descriptive models that provide valid and accurate descriptions of how parts of one problem influence others, often based on mathematical formulation or diagrams. Second, predictive models that aim to forecast future phenomena based on a statistical formulation of historical data. Third, normative models which aim to recommend and find the best solutions for realising the given objective, and which have logically, rationally and morally compelling properties (i.e. axioms) (Keller, 1989). This PhD research study primarily applies descriptive models to describe PECs (RQ1a), information sharing (RQ1b) and their relation (RQ1) in today's whole, and normative models (RQ2) for propositions for effective RP&C (information sharing, forecasting evaluation and order decision-making) in tomorrow's whole.

3.2.2. ABDUCTIVE, INDUCTIVE AND DEDUCTIVE INFERENCE

Critical realism infers from the experienced phenomena to the underlying mechanisms and structures causing the phenomena. Three overall ways of inferring exist (see Figure 3-12). Although not as eminent as deductive inference, the abductive inference is emerging within logistics research (Spens and Kovács, 2006). Following critical realism, abduction was the preferred inferring approach, i.e. the most fitting explanation of observed phenomena.

Figure 3-12. Different inferring approaches used in this study (Spens and Kovács, 2006)



For RQ1, the analysis phase is exploratory and aims to explain phenomena in depth (i.e. PECs' impact on information sharing and RP&C), thus the abductive inference is predominant. When relevant, an inductive and deductive inference may be applied, e.g. confirming initial findings or testing initial results conferring the hermeneutic progression. For abductive inferences, it is desirable to find the underlying causal relations and structures and fit these with the observed phenomena (i.e. nature of knowledge in critical realism). An example of this is Paper #2, where propositions are abductively inferred based on empirical evidence (i.e. real-life observation).

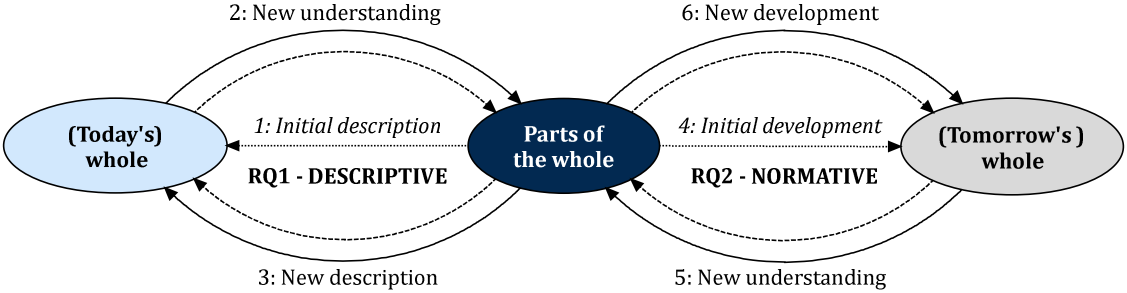
For RQ2, the solution phase is normative and aims to suggest propositions and hypotheses based on prior theoretical knowledge and empirical findings from RQ1, and to test these. Thus, deductive and inductive inference is predominant. When deductive, the theoretical knowledge leads to ex ante hypotheses for testing in order to generate new theory. An example of this is Paper #9, which develops hypotheses for testing real-time sharing (essentially based on the enfolding abductive propositions from Paper #2 and knowledge from Papers #1, #3, #4 and #5). When inductive, the real-life observation leads to hypotheses or propositions without testing. An example of this is Paper #8, which develops theory (i.e. a multi-product inventory control model) based on empirical observations and without testing.

This research studies how to differentiate RP&C of FFPs considering PECs. Thus, a premise is the understanding of e.g. PECs' relation to RP&C. However, although critical realism entails that such understanding is possible (although not representing the truth entirely), it considers the historical and contextual cognition to be outside people's meaning ascriptions. Hence, one PEC may be ascribed a certain meaning and characterisation for one party but be ignored by another (e.g. purchaser or supply chain stage). Considering the PhD researchers' historical involvement with the wholesaler and the (consequent) prejudiced understanding of the parts and empirical phenomena, while striving for minimising subjective bias, the research therefore progresses and evolves through a hermeneutic circular movement.

The hermeneutic circle entails that "all understanding is contextual; i.e. we understand the whole on the basis of its constituent parts, but at the same time we understand the parts because they are elements of this whole" (Brooks, 2013, p. 128). Thus, although it is possible to understand PECs and FFP retailing atomically – and eventually, holistically, as research progress – the true understanding only evolves given a reconciliation with contextual acknowledgement. The circular movement results in a constant increasing validity, constrained by the critical realistic truth criterion: the inference is to be falsifiable under certain and relevant conditions (Brooks, 2013).

In this manner the hermeneutic progression entails that the researcher moves back and forth between understanding and describing (RQ1) – or understanding and developing (RQ2) – the parts of the complex whole and the entire whole, in an ongoing spiral until reaching a complete understanding. This is illustrated in Figure 3-13. Thus, any analysis and reasoning proceeds through a circular inference with continuous validation and adjustment. This PhD study has gone through six flows, starting with the initial description of the parts and ending with proposed development(s) for tomorrow's whole.

Figure 3-13. Operating hermeneutic progressions of this PhD study split into the descriptive analysis and normative solution phase



Overall, for the descriptive RQ1, an initial preconception of the parts, i.e. information sharing, RP&C, FFPs and PECs (based on theory and own empirical knowledge), led to an initial understanding and description of the whole: how PECs impact information sharing during RP&C in FFP retailing (Step 1). This was then verified/rejected through interviews and observations constituting the complex whole, in turn causing an altered and new understanding (Step 2). Then, a new description (Step 3) was made, to be verified/rejected. In a circular progression, Steps 2 and 3 were iterated until reaching a consensus and satisfying understanding (i.e. answering RQ1).

As an example, in Paper #2 (RQ1a), based on a literature study, different PECs were identified. In the attempt to minimise bias, PECs were identified for different industries and planning levels (parts of the whole). Each PEC was then characterised in relation to FFP RP&C based on literature and the researcher's (prejudiced) knowledge (Step 1). Then, interviews and case studies with participating FFP processors were carried out to validate and verify the PECs and characterisation (today's whole). This led to a new understanding about the individual PECs, as well as additional information regarding e.g. which PECs are relevant for which FFPs and what is their impact (Step 2). Based on this, the process was iterated by making a new description of the PECs (Step 3), which was once again validated and verified. This hermeneutic progression allowed for an expanding understanding and knowledge about the parts of the whole (i.e. information sharing, RP&C, FFPs and PECs) and the whole of the parts (PECs' impact on information sharing during FFP RP&C). The iterative verification and validation of understanding unfolded particularly through interviews and case studies for both RQ1a and RQ1b, In an attempt to try to undercover the understanding (RQ1).

Then, for the normative RQ2, an initial development of a solution for tomorrow's whole (differentiated RP&C of FFPs) was suggested based on the abductive descriptive understanding of the current situation, i.e. the new and improved reality conferring the nature of RQ2 (Step 4). After verifying this (by e.g. computing according to developed hypotheses (Paper #9)), a new understanding was created (Step 5) by understanding the discrepancy between the intended and actual outcome, causing changes to the initial development. In this manner, the new understanding (i.e. Step 5) reconciled the abductive descriptive understanding from Steps 1–3, together with the proposed development (Step 4), to report on the intended resemblance and consequent impact. This new and modified/adjusted development was then verified (Step 6), causing yet a new understanding (Step 5). Steps 5 and 6 were iterated until reaching a consensus and satisfying understanding of differentiated FFP RP&C (i.e. answering RQ2), thereby allowing for an understanding of the effective RP&C.

To select the most effective solution, propositions/hypotheses are quantitatively tested and evaluated by means of mathematics and statistics supported by the ongoing inductive and deductive reasoning (i.e. hermeneutic progression). Since these approaches lean towards the methodological stance of critical rationalism[2] and positivism[3] (i.e. outside the chosen paradigm), they are only applied to compare and validate the effectiveness qua RQ2 and consumer requirements in FFP grocery retailing.

3.3. OPERATIVE PARADIGM

The operative paradigm relates to the methodical procedures and methodics applied throughout this PhD study (i.e. methodology). Following Arbnor and Bjerke's (1997) definition (see below), methodical procedure refers to the way of consciously and explicitly choosing e.g. "a technique for selecting the units to study, collecting data, or for analysing results" (1997, p. 16). Methodics concerns the manner in which researchers relate and incorporate the chosen methodologies into a study plan and how the study is carried out (Arbnor and Bjerke, 1997).

> **Definition of methodical procedure:** "the way the creator of knowledge incorporates, develops, and/or modifies some previously given technique in a methodological approach. Adapting and possibly modifying a previous results and/or theory is also called methodical procedure."
>
> (Arbnor and Bjerke, 1997, p. 16)

According to Eisenhardt (1989, p. 537) "theory-building researchers typically combine multiple data collection methods." For the systematic methodical approach in empirical research, Flynn et al. (1990) suggest a framework consisting of different methods. This is based on the specific research design of the specific study. In this PhD research study, the sub-studies mainly govern single and multiple case studies. Case study approaches are often used within retailing/planning literature (see e.g. Dreyer et al., 2018; Ivert et al., 2015; Kiil et al., 2018b). Different methods have been used in the different sub-studies (i.e. Papers #1 – #9); mainly historical archive analysis, observations and interviews (Flynn et al., 1990). The methods are presented in Figure 3-14.

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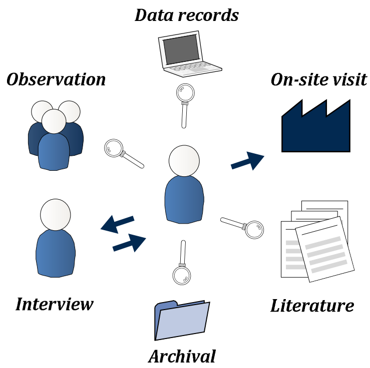
[2] Natural scientific hyper deductive methodology where hypotheses/proposition are scrutinised by empirical testing with the prospect of falsification/substantiation.

[3] Natural scientific empirical inductive methodology where methods are based on quantitative methods and data collection, and analysis is by means of statistics.

Figure 3-14. Methods for data/information collection



While the historical archive analysis relates to the unbiased and historical data that was recorded when "providers of it have no awareness of being observed (…) it may be impossible to obtain the type of data desired" (Flynn et al., 1990, p. 258). This method is particularly used when obtaining knowledge about historical RP&C behaviour, order frequency, order size, etc. The observations were used to obtain knowledge through both being the participating observer (e.g. actual on-site RP&C at wholesaler) and observing observer (on-site visit at FFP processors). Finally, semi-structured interviews were used to obtain (primarily qualitative) information from relevant people to create deep understanding. The final step in the framework is data analysis, where Flynn et al. (1990, p. 264) point out that "it is difficult, if not impossible, to draw conclusions from empirical data and to generalize them, without the assistance of statistical evidence." During the different sub-studies, multiple different methods have been applied, including descriptive statistics (min, max, mean, standard deviation, percentile, variance, etc.), charts, regression analysis, flow diagrams, clustering, correlation and autocorrelation.

Figure 3-15 provides an overview of the different sub-studies of this PhD research (Papers #1 – #9). Split between the analysis and solution phase, the bent full arrows indicate a direct relationship between the papers, the dashed straight lines indicate an indirect relationship, i.e. building upon previous papers, conferring that science is cumulative. The articles are grouped according to the RQ they answer. Following the progression of the PhD research study, Papers #1 and #2 (RQ1a) and Papers #3, #4 and #5 (RQ1b) have complemented each other and together progressed the research in Papers #6, #7, #8 and #9, i.e. the solution phase. The dashed line in the RP&C area indicates that information sharing and order decision-making are related to one another, yet this is not in direct focus as the objective of this research relates to PECs' impact on RP&C. The distribution of papers during the research project period is illustrated in Figure 3-16.

Figure 3-15. Relationship between articles, research questions and the analysis and solution phase

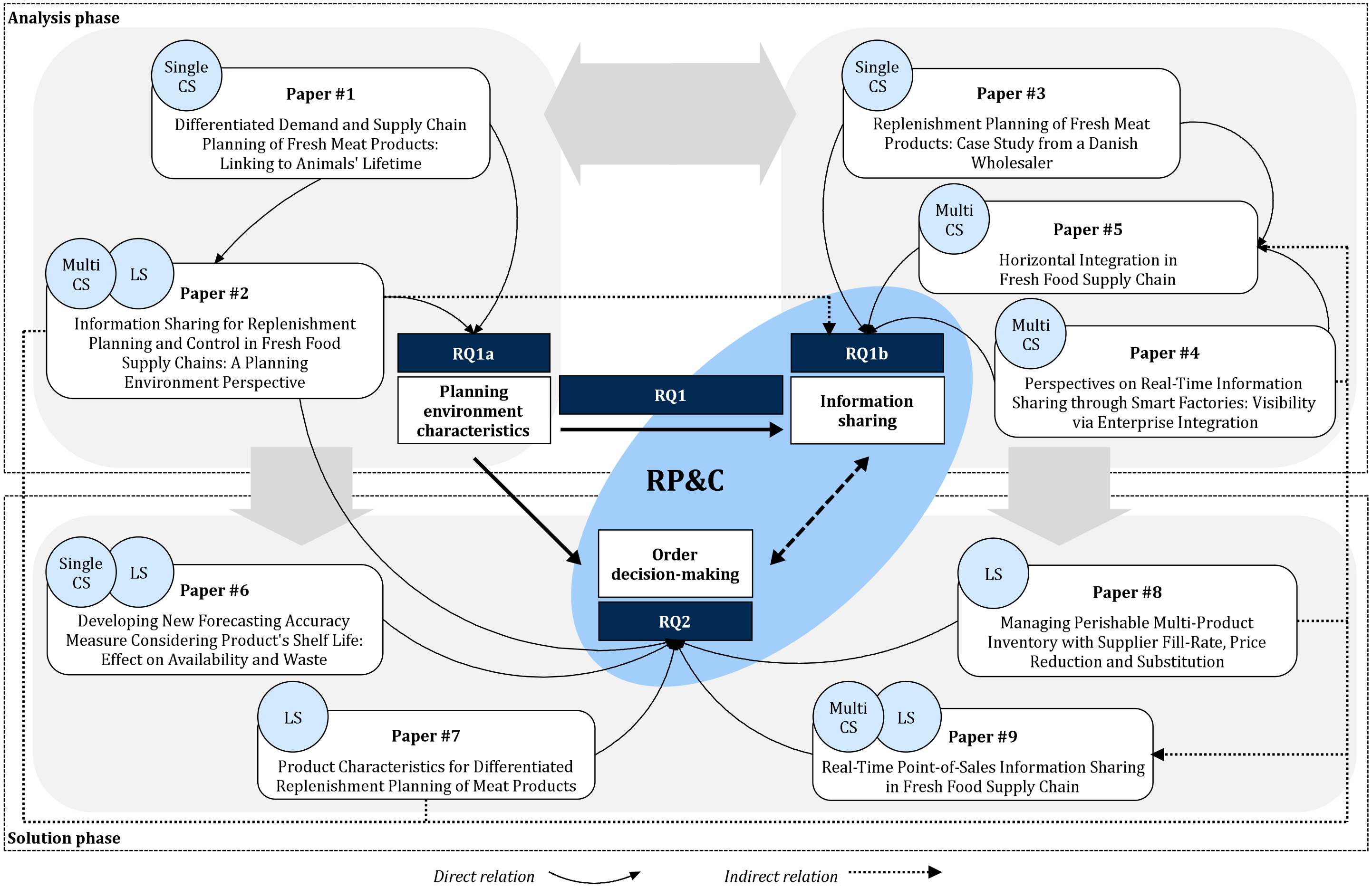
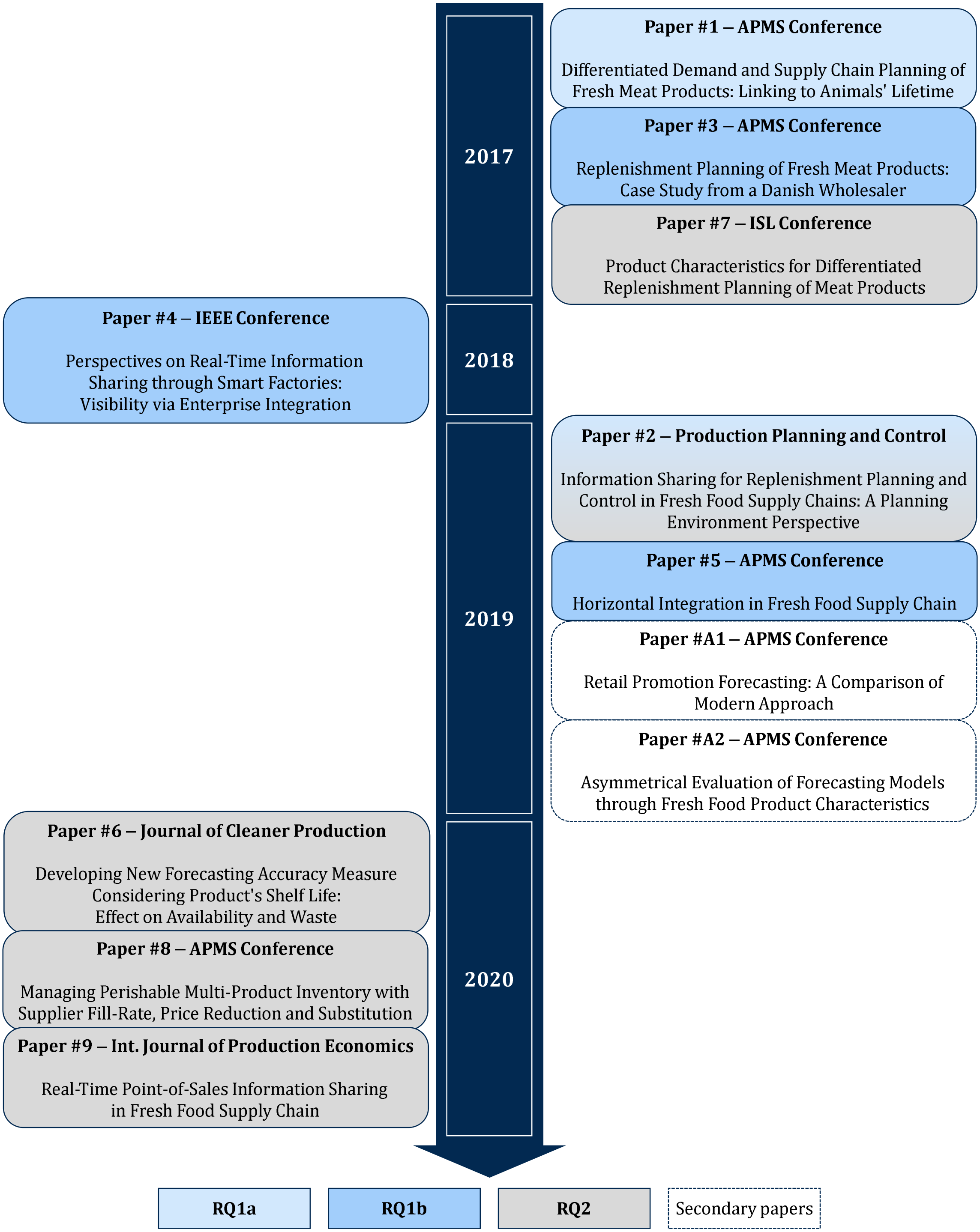


Figure 3-16. Timeline of the papers during the research study



3.3.1. RESEARCH QUALITY

When doing research, there is an interest in conducting and constructing a study that may be subject to additional and/or repetitive treatment in post-time by other researchers (Paltridge and Starfield, 2007). Hence, the research must have a certain level of trustworthiness. Since this research project consists of both theory and empirical observations/data, it is beneficial to discuss the level of reliability and validity. Overcoming the concerns from a positivistic point of view about trustworthiness in empirical studies, Shenton (2004, p. 64) uses four criteria, as defined by Guba, "in pursuit of a trustworthy study." These are credibility, transferability, dependability and conformability. Each is briefly explained in the following, and otherwise discussed as extensions to the operative paradigm for each of the research questions.

Credibility deals with finding out how well the research reflects reality, that is the phenomenon observed. Shenton (2004, p. 64) points out that "ensuring credibility is one of the most important factors in establishing trustworthiness" and presents different ways of assuring this. The predominant methods used in this research study are triangulation, iterative questioning and own background. Since this is a PhD research study, the study has additionally been subject to peer scrutiny, and member checks of data and interpretations/theories found (e.g. during supervision). When triangulating, one seeks to crosscheck and validate obtained information (e.g. data and information) in the attempt to ensure a sufficient level of comprehensiveness and correctness. In this manner, triangulation also helps to minimise the amount of left out/overseen information. Shenton (2004, p. 66) notes that by involving different people (so-called informants), "individual viewpoints and experiences can be verified against others and, ultimately, a rich picture of the attitudes, needs or behaviour of those under scrutiny may be constructed."

In regard to transferability, Shenton (2004, p. 69) points out that it "is concerned with the extent to which the findings of one study can be applied to other situations." Given this, and that this research is based on a few examples of FFP processors (one fish, one chicken and one pork) as well as one wholesaler, the research study has limited comparable empirical evidence (as opposed to work presented by, e.g. Kuhn & Sternbeck (2013) and Hübner, et al. (2013)). However, as Shenton (2004) notices, "if practitioners believe their situations to be similar to that described in the study, they may relate the findings to their own positions." Yet, although the consideration and description of the context as such allows researchers in post-studies to see the extent to which something is transferable, or not, to their study, the constructivist influence on the paradigmatic stance entails the understanding about delimiting and limiting factors potentially having an impact on the inferred results. Thus, to support this, and following Shenton (2004), information is provided about faced restrictions in the data, the number of participants involved, data collection methods, number and length of data collection, etc.

Dependability governs the degree to which results and observations can be replicated or repeated (Shenton, 2004). As an empirical study, the results and observations heavily rely on the exact context in which phenomena are observed. However, factors such as environment, settings and goals may change over time. In fact, peoples' attitude and way of influencing observed phenomena may vary depending on sociological factors like mood. Shenton (2004, p. 71) notes that to overcome this, "processes within the study should be reported in detail, thereby enabling a future researcher to repeat the work, if not necessarily to gain the same results."

As to the extent to which findings in the study are neutral, that is, solely influenced and shaped by informants and people involved, confirmability concerns the bias, motivation and/or interest in undertaking the study.

The following discusses the methodical procedures for each RQ in general relation to the individual papers. Certain papers have contributed to more than one RQ, thereby appearing under more than one RQ and applying different methodical procedures. Therefore, the relevant parts will be presented at the respective RQs. Table 3-9 at the end of the section may be used as complementary, to ensure an overview of the different data collected during the different sub-studies.

3.3.2. RESEARCH QUESTION 1

To answer the analysis-oriented RQ1, sub-questions RQ1a and RQ1b were raised, aiming to understand PECs and information sharing, respectively. Synthesising the answers from sub-questions RQ1a and RQ1b is expected to answer RQ1. The following thus presents the general methodical procedures and methodics for each of the two sub-studies. For detailed information about the operative paradigm in the different sub-studies, see Papers #1–#5.

> **RQ1**: How do planning environment characteristics impact information sharing during replenishment planning and control in fresh food retailing?

The first research question concerns identifying and broadening the understanding of FFPs' PECs:

> **RQ1a:** What are the planning environment characteristics in fresh food retailing, and how are they characterised?

To ensure background understanding, an exploratory search of the literature was conducted in order to find PECs. This resulted in almost 100 different PECs, governing several different areas of planning and industry. After selecting the relevant PECs, namely product, demand, supply and production, an empirical multiple case study was designed and undertaken. This was done since the literature lacks the identification and verification of context-relevant PECs. A case study approach was selected as it allows for the handling of multiple types of information/evidence (e.g. observations, mapping, interviews, documents, etc.) and examining the phenomena in natural contextual settings (Eisenhardt, 1989; Voss et al., 2002; Yin, 2014). As this PhD research study focuses on the triadic supply chain constellation, single (Paper #1) and multiple (Paper #2) case studies (in particular, observations and semi-structured interviews) were designed to investigate FFP processors, wholesaler and retail stores, to identify and verify the relevant PECs. The complete interview guides for each stage are presented in Appendix C. For the on-site observations at FFP processors, the researcher was guided through the production facilities with a company representative who explained the different processes, the raw-material characteristics and their impact on the processing. Based on mappings of the processing stages from the FFP processor' supplier (farmer) until POS, as well as the identification of PECs impacting sourcing and processing at the FFP processor, the research continued behind desk with the analysis and synthesising of (preliminary) findings. Here, descriptions of the PECs were made, along with mapping where the impact is found. These were then verified and adjusted through a hermeneutic circular abductive inference, i.e. the most fitting explanation to observed PECs was verified/rejected by the FFP processors. This hermeneutic progression was similar for wholesaler and retail stores, when identifying the PECs impacting RP&C decision-making at wholesaler and retail stores.

The collected data for answering RQ1a is depicted in Table 3-9, where particularly qualitative information (i.e. interviews) have been used. Quantitative information was primarily used for selecting products in the individual studies and obtaining product information (master data) so as to e.g. group the products according to meat-type and/or FFP processors.

The second research question served to provide in-depth understanding of information sharing in FFP grocery retailing:

> **RQ1b:** How is information sharing during replenishment planning and control in fresh food retailing characterised?

In parallel with the research undertaken for RQ1a, a literature study was carried out to understand information sharing and create a theoretical framework. To understand how information sharing is characterised, the literature was first explored and examined in terms of information sharing in current RP&C frameworks in grocery retailing. This led to eight different frameworks (discussed in Section 2.1) and several comparative studies pointing out how information sharing differs across the frameworks. However, the studies and frameworks merely provided a generic understanding of information sharing and how it differs at a product group level according to demand type or supplier.

Considering the FFPs' PECs, and to provide a more effective understanding, case studies were designed and carried out to investigate how information sharing is characterised empirically and to what extent it differentiates according to context, as described in the literature. The use of a single case study (wholesaler in Paper #3) and multiple case study (Papers #4 and #5) aimed to increase the validity by examining and verifying what/how/when information is shared empirically, considering the context of FFPs (Yin, 2014).

To ensure that the interviews regarding information sharing were not biased and influenced by e.g. different moods and emotions (Schein, 1999), compared to the interviews regarding PECs (constructivist reflection in critical realism), the interviews regarding information sharing were carried out in parallel with the interviews regarding PECs (RQ1a). The interview guides found in Appendix C was used. Based on the mappings from RQ1a, the information flows and decision-making processes were added, behind desk, along with the identification of which individual processing stages throughout the supply chain the information relates to. Findings were verified and adjusted through hermeneutic circular abductive inference, i.e. the fittest explanation to reported information sharing was verified/rejected by the individual case participants, FFP processors, wholesaler and retail stores.

The data collected for answering RQ1b is presented in Table 3-9, where particularly qualitative information (i.e. interviews) was used. Quantitative information was primarily used for selecting products in the individual studies and obtaining product information (master data) so as to e.g. group the products according to meat-type and/or FFP processors.

3.3.2.1 Research Quality of RQ1a and RQ1b

To strengthen the research as well as the validity of answering RQ1, multiple products and different parties were included (Eisenhardt, 1989; Flynn et al., 1990). However, this was always done according to the principle that the theory must be falsifiable under relevant conditions (i.e. the criterion of validity in critical realism) (Brooks, 2013). The use of multiple case studies allows for a deeper understanding of the PECs and information sharing, while the differences across cases allow cross comparison across different product, supply and production types.

Credibility: The applied methodical procedures and methodics are considered to provide the research with a high level of credibility. As discussed above, the credibility of this research study is mainly related to triangulation, iterative questioning and own background. As part of the theory building process, triangulating and comparing empirical observations against theoretical descriptions contributes to the falsification process and the construct of validity (i.e. the criterion of validity within critical realism). During the answering of both RQ1a and 1b, findings and results were cross-checked and validated against both theory and empirical case studies. The triangulation against existing theory ensured a constant reflection on 'what is already known' and subsequently a validation towards whether observed PECs are already understood in theory (i.e. discussed in previous studies) (RQ1a) and whether empirical information sharing is reflected in theory (RQ1b). The triangulation against the empirical case studies allowed for confirmation of the research's perception of reality (i.e. critical realist ontology) and broadened the understanding of PECs and information sharing, conferring the hermeneutic progression of ensuring a correct reflection of reality (i.e. going back and forth between what is observed and what is understood; Figure 3-13 in Section 3.2).

Iterative questioning was also used to achieve higher levels of correctness and comprehensiveness. Key-questions were asked a minimum two times, to different informants and/or separated by certain time periods. For the majority of case studies, this meant that questions were raised both during the first interview (for exploring and creating (initial) understanding) and during the second interview (for ensuring and deepening understanding). Certain questions considered critical for understanding were also asked after some period following a longitudinal approach (discussed shortly). The identified gaps from interviews, meeting, observations, etc. were investigated and further elaborated/eliminated through follow-up questions. The iterative process continued until a consensus and/or uniformity in answering was reached. This iteration improved the credibility by both clarifying whether the researcher did/did not understand the observed phenomena (i.e. PEC and information sharing in focus), but also diminished the potential of misunderstanding the question due to incorrectly phrasing/proposing of the question and/or intrapsychic perception (discussed shortly). In situations where the researcher did not consider the understanding complete and/or comprehensive, the same questions were not only raised again, they were also asked in different ways to ensure credibility (Bryman and Bell, 2015).

Finally, the researcher's relation and experience within the participating wholesaler (more than 13 years employment) led to increased access to e.g. retail stores and FFP processors, in turn increasing the credibility of findings. Despite the researcher's history with the wholesaler, and thus somewhat high level of biasness, the use of triangulation, hermeneutic progression and iterative questioning are believed to reduce bias and subjectivity, although complete apprehension is not possible (i.e. the epistemological stance in critical realism).

As the PhD research study lasted three years, longitudinal follow-ups to the analyses and findings were possible. This ensured a generally higher level of research credibility from a paradigmatic stance. This is the case, since verifying findings separated by different time periods encompass the constructivist reflection that reality changes when the (researcher's) cognition thereof changes. In particular, the ongoing intrapsychic processes during the research (i.e. the ORJI cycle[4]), entail that any intervention with a person (interview, observations, etc.) imposes a perceptive change in both the researcher and the researched (employees). As an example, during interviews, the word "problem(s)" was avoided and instead "challenge(s)" was used, due to the linguistic perception of "problem" (negatively loaded) versus "challenge" (positively loaded). Schein (1999, p. 91) points out that although "one's judgement is logical it is based on 'facts' that may not be accurate, hence the outcome may not be logical at all." Reflecting this onto the ontological and epistemological stance in critical realism, the perception of a stratified world from which the researcher cannot completely apprehend, i.e. not act completely objectively, thus raises the notion of the maxim that the researcher may be influenced by initial and premature attributions and prejudgment, in turn influencing the findings. Conversely, the longitudinal approach and hermeneutic progression is believed to minimise the impact.

Although the credibility of the operative paradigm for RQ1a and 1b is considered high given the (delimited) methodology of critical realism, it is valuable to also briefly reflect of the credibility in relation to other paradigmatic stances. This is the case, since the paradigmatic stance defines and delimits the degree to which the research can obtain understanding and avoid impacting on the researched phenomenon, since the ontological and epistemological stance delimits the applied methodology and thus reflects the philosophical view of how to obtain knowledge. As an example, a positivistic paradigm entails an objective and researcher-free world, where the truth can be reflected and described with complete objectivity.

Transferability: In terms of transferability, it is considered both relatively low and relatively high, depending on the focus. For transferability in general, critical realism's ontology entails that the researcher's cognition and understanding of reality is historically and contextually based. Thus, for critical realism, transferability in general is influenced by a ceteris paribus approach. Hence, an underlying premise for transferring the study to other situations within critical realism is that the context must remain the same. In this study, there are differences in transferability, depending on which aggregation level is referred to.

At a perishable products category level, the transferability of both RQ1a and 1b is considered relatively high, since they encompass five FFP processors and nine retail stores/an entire retail chain. Only for the wholesaler is the general level of transferability considered low, since only one case represents this supply chain stage. More specifically, following critical realism and hermeneutic progression,

[4] As we simultaneously operate as a data-gathering system, a processing system and a proactive managing system, the ORJI cycle constitutes that "we observe (O), we react emotionally to what we have observed (R), we analyze, process and make judgments based on observations and feelings (J), and we behave overtly in order to make something happen – we intervene (I)" (Schein, 1999, p. 86).

empirical findings related to e.g. information sharing between wholesaler and retail stores (thus abductive inference) reflect certain underlying premises such as e.g. daily deliveries, organisational structure and decentralised decision-making. As an example, while centralised decision-making (as in corporate owned retail chains) entails the wholesaler as the order decision-making unit for retail stores, decentralised decision-making (in franchise-based retail chains) entail the retail stores as the store order decision-making unit. Thus, while RP&C in centralised constellations entails less uncertainty in the RP&C as to actual store orders (size and time), considering that wholesaler per se can plan certain amounts of time into the future, RP&C in decentralised constellations impose a relatively larger uncertainty. However, since this research project is industrial, in collaboration with the wholesaler, the option of including other wholesalers did not seem possible.

At the meat-type level, the transferability in relation to RQ1a is considered relatively low since the research study contains few FFP processors. This means that the PECs identified at e.g. the fish FFP processor have a relatively lower chance of being valid and/or applicable to another fish FFP processor, since only one fish FFP is included. Conversely, for RQ1b, the transferability is considered high, mainly due to the current identical manner of sharing information regardless of the meat-type, i.e. there are several cases to verify findings.

At product level for RQ1a (i.e. the PECs identified for the different products), the research possesses high transferability for certain products (e.g. ground meat and cut meat FFPs) due to the number of individual products included. However, for 'special' products such as marinated FFPs, the portion of products included was relatively smaller (qua assortment of wholesaler), resulting in fewer products for ensuring that the findings are applicable to other situations, i.e. the same type of products at different FFP processors. For RQ1b, the same manner of sharing information regardless of the individual product also entails high verification of observation and understanding, thereby providing a greater generalisability. This is the case since the epistemological stance in critical realism entails that it is possible to obtain knowledge about the fundamental mechanisms, and not only the observed phenomena (Brooks, 2013).

Dependability: The methodical procedures and methodics of the research study are considered to have a high ability of being replicated/repeated. For both RQ1a and 1b, since the PECs/information sharing were/was identified through semi-constructed interviews with available interview-protocols (Appendix C), and rigid mapping tools were used, with description in the relevant papers, the (new) external researcher may repeat the same research and obtain thee same findings. Naturally, with the acknowledgement that science is cumulative, and no objective research exists in critical realism (e.g. the ORJI cycle as discussed above), this means that if replicating the same research on the same case participants, the ontological and epistemological stance in critical realism entails that the observable/interviewee is already influenced by knowledge from the previous research study. The observable/interviewee has been influenced by e.g. additional/new information, thereby diminishing the foundation for ensuring an identical base for conducting the new study in the first place.

Further, acknowledging that the world changes as well as the critical realistic epistemology, it must be recognized that the dependability is generally influenced by changes made by case participants throughout the research study (i.e. three years). In particular, during the period of the research study, the wholesaler had changed the RP&C setup. While the RP&C was characterised as one cycle when the study started (actual store orders were aggregated upon receival by the wholesaler and forwarded to the FFP processor), during the study the RP&C changed into two cycles (the wholesaler forecasts demand and store orders FFPs before actual orders from stores are received). Further, during the old RP&C setup, retail stores were divided into two groups with three deliveries per week, either Monday-Wednesday-Friday or Tuesday-Thursday-Saturday, so-called MWF- and TTS-stores. In the current setup, all retail stores may order and receive products seven days per week. Obviously, such a fundamental change influences the project, and in particular the information sharing.

Confirmability: From a critical realist point of view, the confirmability of the research study is considered moderate. From an ontological point of view, critical realism entails that although an objective reality is assumed to exist, it is stratified and to some extent influenced by the researcher acknowledging that objective research does not exist. Only pure positivism considers complete confirmability (i.e. complete objectivity and no influence from the researcher on researched). In this manner, the more constructivist the ontology and epistemology, the less confirmability is present. However, due to methods for obtaining high credibility (triangulation and iterative questioning), it is believed that certain objectivity (thereby confirmability) is achieved. Yet, it must be acknowledged that the use of interviews is a constructivist approach entailing, from an ontological point of view, that reality is merely a social construction continuously created by the interactions between individuals (e.g. the ORJI cycle).

3.3.3. RESEARCH QUESTION 2

While RQ1a and 1b concerned the analysis phase of the PhD research study, RQ2 concerns the solution phase of the study. The following thus presents the general methodical procedures and methodics used for answering RQ2. For detailed information about the operative paradigm in the different sub-studies, see Papers #6–#9. The reader may use Table 3-9 (at the end of this section) in parallel when reading the following, in order to switch between the details and overview.

> **RQ2**: How can wholesaler effectively plan and control replenishments according to the fresh food planning environment characteristics, and what is the impact on performance?

To develop a solution, i.e. answer RQ2, the background understanding from RQ1 was used for creating sub-studies reflecting solutions related to each of the three areas of which RP&C consists: (demand) information sharing, forecast evaluation and inventory control. During each of these, PECs were considered in terms of greatest impact on product level differentiation. That is, PECs entailing only little differentiation in the RP&C were eliminated, to ensure focus on those with greater impact. This selection was based on the understanding of PECs and responses from interviews. For information sharing, the understanding of how different FFPs have different PECs, and thus different needs regarding information sharing, led to the abductive suggestion of 19 propositions. The propositions were generalised from observed PECs and linked to different information sharing facets (and sub-facets). In particular, the use of real-time information appeared to be beneficial in certain situations. However, considering that a continuous flow of real-time information is not appropriate, interest was in testing and verifying real-time information sharing in terms of the timing for sharing real-time information. A multiple case study was carried out with empirical data of 50 products. This founded the basis for computing and analysing the impact of real-time information sharing across multiple different time points as well as the abductive inference of propositions for when to use real-time sharing and when not to, based on the consequent value (i.e. impact on performance). For the forecasting evaluation, interest was in exploring asymmetrical evaluation considering the impact of shelf life on product availability and freshness. Based on a case study, a new forecasting accuracy measure was developed and then verified through testing on empirical data from 17 products. For the inventory control, current frameworks in the literature were investigated. In particular, one heuristic for inventory control of FFPs was expanded to include different key PECs. Although not empirically tested, the proposed methodology was verified by a wholesaler.

The data collected for answering RQ2 is presented in Table 3-9, where particularly quantitative information was used for testing and verifying the proposed solution. Qualitative information was mainly used indirectly, in the background understanding from the answering or RQ1.

3.3.3.1 Research Quality of RQ2

Likewise for RQ2, multiple products and different parties were used to strengthen the research as well as the validity of the answer (Eisenhardt, 1989; Flynn et al., 1990). A general premise for high quality in RQ2 is obviously a higher level of quality in RQ1, since RQ2 builds on the knowledge from RQ1, following the garbage-in-garbage-out principle. Thus, the following discusses quality under the assumption that the quality in RQ1 is adequately high so as not to diminish the findings of RQ2.

Credibility: From a science perspective, the applied methodical procedures and methodics are fundamentally considered to bring the research a high level of credibility, since it relies on already demonstrated studies (i.e. knowledge is cumulative). Following critical realism, from its positivism-influenced area, science is cumulative and accumulates into an increasingly certain "body of knowledge" (Brooks, 2009). Unlike certain positivistic research areas, such as operation research where it assumed that reality can fully be described through e.g. a distribution-based approach (i.e. high statistical credibility, e.g. inventory models), this PhD research study acknowledges the inability to completely reflect reality and the consequent need for empirical evidence (the critical realist ontology). Although Paper #6 relies on simulating forecasting errors (conferring the inclusion of quantile-based evaluation), Paper #8 uses a heuristic approach rather than a control model to reflect that the assumption that a known distribution of demand is not true. Further, in Paper #9, the computation enriched the credibility by providing a one-to-one comparison, i.e. if the data was shared accordingly, given the described constraints (in the paper), then the performance would have been accordingly similar. Thereby ,the shortcomings of e.g. simulation were overcome. Thus, the credibility in the solutions of RQ2 are considered and reflected as much in terms of empirical verification as in terms of statistical verification, if not even more so.

Triangulation was used to ensure a high level of credibility, i.e. the solution addresses and solves actual needs. During the answering of RQ2, particularly triangulation was used to ensure credibility. Initial developments and sketches thereof were thus evaluated and verified against both theory and empirical case studies. Triangulating against theory ensured a constant reflection on whether the proposed solutions/developments already exist (i.e. novelty). The triangulation against empirical cases allowed assurance that the proposed developments/solutions are appropriate and useful in an empirical setting.

Transferability: In terms of transferability, it is considered high within the research area of perishable meat products. As discussed above, transferability within critical realism entails a historical and contextually-based cognition with a ceteris paribus approach, i.e. transferability is high when considering products identical to those investigated in this research study. As with RQ1, differences in transferability thus depend on the aggregation level referred to.

At a general level, i.e. perishable products versus non-perishable products, the transferability is considered low, since key PECs such as perishability, shelf life and animal growth time are irrelevant to non-perishable products (e.g. steel plates, wood pieces, etc.). In addition, at a general level, the businesswise ontological stance of this PhD research study may influence the transferability.

The wholesaler and retail stores in this study represent an independent wholesaler (dealing with multiple different customers and store-concepts) and franchise-based retail stores. This entails e.g. decentralised decision-making (since each store is managed/owned by the franchisee), as opposed to capital-chain-based retail stores with centralised decision-making. Thus, since the solutions in this PhD research study are created in light of the wholesaler only being able to propose orders (which stores then have to confirm), the solutions may require minor adjustments if applied to e.g. distribution centres with capital-chains where automated order generation is applied. Finally, at a general level, following the constructivist reflection in critical realism, the transferability of the solutions across other cultures may face certain challenges. As an example, the proposed forecasting accuracy measure in Paper #6 represents a penalisation process in which each product is evaluated in terms of the consequence from under-/over-forecasting. This valuation of penalties is obviously influenced by sociological factors such as seniority and experience. Thus, while the proposed forecasting accuracy measure may be directly and appropriately transferable to an experienced purchaser, it may/may not be so for a new inexperienced purchaser. Then, an obvious question regarding this would be, "why not systemise the penalisation according to a rule?". Following critical realism, reality is complex and it is not possible to model it in its entirety, hence the human evaluation increases the credibility of the reflection of reality. For example, there is a significant difference in over-forecasting pork roast during summer (consumers are on vacation or prefer BBQ items, sausages, steaks, etc.) versus in the beginning of December (consumers buy pork roast as part of national Christmas dinner in Denmark) versus the end of December (consumers buy beef products for New Year's).

At meat-type and product level, the transferability of RQ2 is considered high, since the solutions are developed according to the maxim of differentiating RP&C according to FFPs' PECs. This is the case, since the epistemological stance in critical realism entails that it is possible to obtain knowledge about the fundamental mechanisms, and not only the observed phenomena (Brooks, 2013).

Hence, while the transferability of suggested solutions is low to non-perishable products, and potentially low for other FFPs (due to differences in characteristics), it is considered high for the four meat-types in focus, namely beef, pork, chicken and fish products. In this manner, the increase of transferability in RQ2 is oppositely proportional to the aggregation, as with RQ1. While a high aggregation level entails high transferability for RQ1, a high aggregation level entails low transferability for RQ2 – and vice versa.

Dependability: The methodical procedures and methodics used to develop the suggested solutions are generally considered to provide the research quality of RQ2 with a high level of dependability, since it is based on an expansion of previously tested and proved theories, however, with the precaution of potentially being falsifiable (the validity criterion in critical realism). Since dealing with e.g. forecasting models when testing the suggested forecasting measure (Paper #6), it should be noted that the forecasting model optimisation relies on a stochastic perception of demand. This means that if replicating the same research with the same case participants, the stochastic element may yield different results; not identical, but similar results are assumed to appear.

Confirmability: Given the paradigmatic stance within critical realism, please see RQ1.

Table 3-9. Data collected for different research studies

Type	Data collected	RQ1a		RQ1b			RQ2			
		Paper #1	Paper #2	Paper #3	Paper #4	Paper #5	Paper #6	Paper #7	Paper #8	Paper #9
Data records	Agg. store demand, ordered (12m/453p)	x				(x)	(x)			(x)
	Agg. store demand, normal + campaign, ordered + delivered (12m/201p)			x						
	Agg. store demand, ordered (12m/17p)						x			
	Detailed POS sales, 333 stores product/time/day/store (2m/63p)									x
	Store order, normal + campaign, ordered + delivered (12m/53p)									x
	Supplier order, ordered + delivered (12m/53p)									x
	Supplier production information (2m/53p)									x
	Wholesaler inventory level, (2m/53p)									x
	Master data (453p)	x				(x)	(x)			(x)
	Master data (201p)		x	x						
	Master data (53p)									x
	Master data (17p)						x			
Obser-vations	Production facilities (FFP processor)	x								
	Ordering process and software (wholesaler)	x	x	x	(x)	x	(x)			(x)
	Ordering process and software (retail store)	x				x				(x)
Work-shop	Verify findings and data from interview(s)	x	x	x	x	x	x			x
	Impact from inaccurate forecasting (penalisation)						x			
Inter-views	Sales responsible, Beef #1	x				x				(x)
	Production planner and scheduler, Beef #1	x				x				(x)
	Senior sales manager, Beef #2	x				x				(x)
	Vice president, Beef #2	x				x				(x)
	Sales director, Pork	x				x				(x)
	Customer care manager, Pork	x				x				(x)

Type	Data collected	RQ1a		RQ1b			RQ2			
		Paper #1	Paper #2	Paper #3	Paper #4	Paper #5	Paper #6	Paper #7	Paper #8	Paper #9
	Key account manager, Chicken	*x*				*x*				*(x)*
	Supply chain manager, Chicken	*x*				*x*				*(x)*
	Demand planner, Chicken	*x*				*x*				*(x)*
	Director, Fish	*x*				*x*				*(x)*
	COO, Wholesaler	*x*				*x*				*(x)*
	IT manager, Wholesaler					*x*				*(x)*
	Procurement manager, Wholesaler	*x*	*x*	*x*		*x*	*x*	*(x)*	*(x)*	*x*
	Purchasing assistant #1, Wholesaler	*x*						*(x)*	*(x)*	
	Purchasing assistant #2, Wholesaler					*x*	*x*		*(x)*	
	Purchasing manager, Wholesaler	*x*				*x*	*(x)*		*(x)*	
	Purchaser #1, Wholesaler	*x*	*x*	*x*			*(x)*	*(x)*	*(x)*	
	Purchaser #2, Wholesaler	*x*				*x*	*(x)*		*(x)*	
	Purchaser #3, Wholesaler	*x*				*x*	*(x)*		*(x)*	
	Warehouse manager, Wholesaler	*x*						*(x)*	*(x)*	
	Franchisor #1, Retail chain	*x*				*x*				
	Franchisor #2–9, Retail chain	*x*				*x*				
Comple-mentary	Qualitative (layouts, presentations, documents, screenshots, etc.)	*x*	*x*			*x*			*(x)*	*(x)*
	Quantitative (statistics, reports, plans, etc. from ERP, WMS and BI systems)	*x*	*x*		*x*					*(x)*

Note: Use of data collected: *x* = directly, *(x)* = indirectly
Data records: m = months, p = products

3.4. CASE STUDY PARTICIPANTS

Several different companies were included in this research study: five FFP processors, one wholesaler and one retail chain represented by nine retail stores (in the qualitative studies) and 333 retail stores (in the quantitative studies). The following briefly outlines the different companies and provides a general introduction in relation to FFP demand. A summary of each case study is provided in Table 3-10.

Supplier Beef1 is a medium-sized slaughtering and processing company with different (specialised) production facilities across the country, delivering (the smallest amount of) products to the wholesaler. Beef2 is a large Danish slaughtering and processing company with several different production sites across the globe, delivering by far the largest number of products to the wholesaler through specialised domestic facilities. Pork is part of a large-sized processing company with facilities across the globe, delivering products through one domestic facility. Poultry also delivers through a single national facility and is part of a large international slaughtering and processing company. Fish is a privately owned seafood processing company sourcing from different fishermen through different national fish auctions. While Beef1 delivers to national customers, the other suppliers also deliver to customers worldwide. All suppliers (except Fish) process national raw material, resulting in only a few hours transport before slaughtering.

The wholesaler serves stores across the country and is considered the largest grocery wholesaler in Denmark. The wholesaler is owned by the same mother organisation as the retail chain, one of Scandinavia's largest players in the grocery market, and the biggest in the convenience market. As part of the value-driven management, the retail stores in the retail chain are driven on a franchise basis. In this way, all stores are individually run by the franchisees, who also own their inventories.

In franchising, individual store-owners (franchisees) manage retail stores according to a set of rules set by the retail chain (franchisor), and it is per se not possible to induce centralized decision-making (Beshel, 2010). Instead, order proposals based on a centralized understanding of demand and supply may be shared with the stores, which in turn have complete autonomy to change, adjust or reject this proposal. As part of the franchise agreement, the stores operate with different assortments of products, which may chiefly be grouped as mandatory and optional. This explains the different number of products between the stores. Further, due to the franchise context, mere centralised decision-making as applied in automated replenishment control (ARP) is not possible per se. The contractual agreements with the stores limits the conventional push-down strategy, which is otherwise widely exploited in the grocery business by so-called corporative retail chains. Rather, decentralised decision-making is applied, with the option for proposing order sizes to the stores.

Table 3-10. Case features of participating companies

Case study	Market scope	Type of customer	Supplier base	# FFP SKUs delivered	# boxes sold in one year (2017 to 2018)	Product types in assortment
Beef1	national	retail chains, stores, butchers, wholesaler	national farmers and slaughter-houses	14	247,000,000	cattle, veal, beef, mix FFPs
Beef2	national, global export	retail chains, stores, restaurants, butchers, food service, wholesaler, meat processors, export	national farmers (unitholders)	75	2,152,000	cattle, veal, beef, organic beef, supreme, mix FFPs
Pork	national, European export	retail chains, stores, hotels, restaurant, butchers, food service, wholesaler, meat processors, export	national farmers and slaughter-houses	47	867,000	pork, organic pork, mix FFPs
Poultry	national, Nordic export	retail chains, stores, restaurants, food service, wholesalers and export	national farmers	26	325,000	poultry, organic poultry, mix FFPs
Fish	national, European export	retail chains, fish stores and wholesalers	auctions and farmers	42	757,000	seafood, mix FFPs, ready-to-eat FFPs
Whole-saler	national	retail chains, convenience chains, stores, export	national FFP processors	303	89,646,000	cattle, veal, beef, supreme, organic beef, pork, organic pork, special pork, pork-veal, organic pork-beef, mix FFPs, conventional poultry, organic poultry, seafood, and ready-to-eat FFPs
Retail store 1-9	Zealand, Jutland	consumers	Wholesaler	269-289	206,000-535,000	

3.4.1. DEMAND CHARACTERISTICS & INFORMATION SHARING

The RP&C process at the wholesaler is characterised as follow. First, the wholesaler creates an order in the purchase planning system (PPS) and sends it to the supplier via ERP by 16:00 at the latest (day 1). After confirmation (via ERP), the supplier schedules the order for production during the night/following morning and delivers to the wholesaler between 06:00 and 13:00 (day 2). While the production still runs (supplier) and FFPs are received (wholesaler), stores create orders in their ERP via hand-terminals and send to retail chains' ERP by 11:00 at the latest (day 2). The store orders are then transferred to the wholesaler's ERP and to the warehouse management system (WMS), releasing orders for picking from 14:00, in two batches (dependent on delivery times to stores). The FMPs are physically delivered to the stores between 18:00 (day 2) and 05:00 (day 3). This results in a lead-time of down to 14 hours for the wholesaler, and down to seven hours for stores, from sending the store order until receiving the delivery. The demand fluctuates throughout the year, and Figure 3-17 illustrates the demand for sales units in retail stores during one year for the 50 FFPs which were included in the sub-study in Paper #2.

Figure 3-17. Daily POS demand for the 50 FFPs included in Paper #2, one year

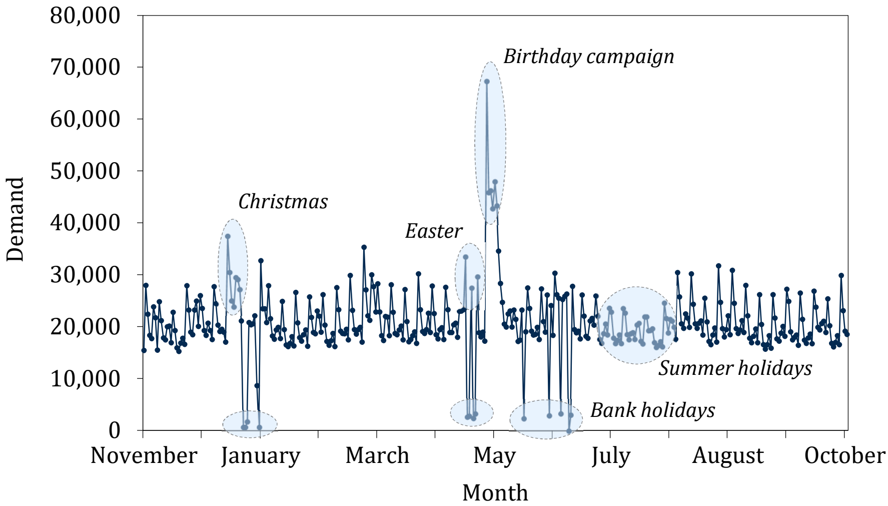
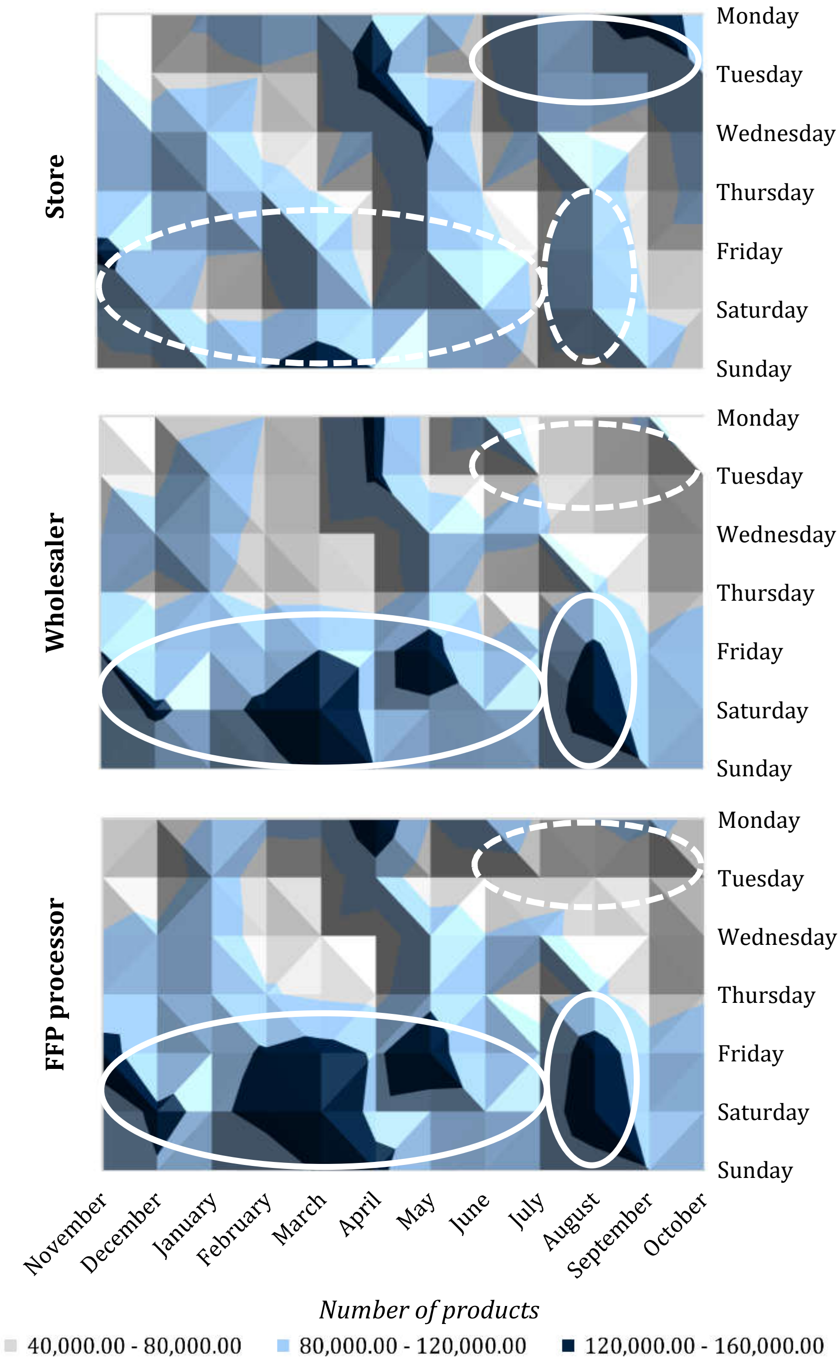


Figure 3-18 illustrates this demand for products (i.e. handled packet size) summed across weekdays and months for each supply chain stage for the same 50 FFPs. While the grey areas indicate a relatively lower demand (i.e. fewer products), the dark blue indicates a relatively higher demand. In Figure 3-18, the white circles highlight examples of how demand is dispersed across the days, i.e. products are delivered in the store on the day after arrival at the wholesaler. For the wholesaler and fresh food processors it is particularly evident that the end of the week is characterised by higher demand, while it is more evenly distributed in the store.

Figure 3-18. Total demand per day per month at supply chain stages for the 50 FFPs included in Paper #2, one year



4

PLANNING ENVIRONMENT CHARACTERISTICS' IMPACT ON INFORMATION SHARING

The purpose of this chapter is to present and discuss the findings related to RQ1 and the two sub-research questions RQ1a and RQ1b. This chapter advances the understanding of planning environment characteristics (PECs), information sharing and how PECs impact the demand and supply information sharing between fresh food product (FFP) processors, wholesaler and retail stores during replenishment planning and control (RP&C).

> **RQ1**: How do planning environment characteristics impact information sharing during replenishment planning and control in fresh food retailing?

>> **RQ1a:** What are the planning environment characteristics in fresh food retailing, and how are they characterised?
>>
>> **RQ1b:** How is information sharing during replenishment planning and control in fresh food retailing characterised?

This chapter comprises three sections. First, Section 4.1 presents the empirical findings related to RQ1a regarding pertinent PECs for the different FFP processors, the wholesaler and the retail stores, based on the findings from sub-studies concerning Papers #1 and #2. Next, Section 4.2 presents the empirical findings related to RQ1b regarding information sharing and its characterisation in fresh food retailing, based on the finding from sub-studies concerning Papers #3, #4 and #5. Thereafter, these two sections constitute the frame for Section 4.3, which synthesises the findings into answering the overall RQ1. Each section ends by consolidating and discussing the empirical findings in relation to the current stance in the literature as presented in Section 2. Additionally, managerial implications are pointed out when appropriate. Detailed analyses are intentionally left out, and the reader is referred to the individual papers for this purpose.

4.1. PLANNING ENVIRONMENT CHARACTERISTICS

Many different PECs impact information sharing during replenishment planning and control (RP&C). The PECs considered relevant to this PhD research study relate to product, demand, supply and production, as outlined in Section 2.4. Empirical case studies have been undertaken to explore whether and in which manner the PECs identified in the literature affect the RP&C at FFP processors, wholesaler and retail stores in fresh food retailing. Further, the case studies provide the foundation for identifying any additional PECs pertinent to the meat and fish context.

During the sub-studies, it was found that most FFPs are processed-to-order daily at the FFP processors, with daily deliveries to the wholesaler. Shortly after being received by wholesaler, the FFPs are picked and packed before being distributed to retail stores. In this way, the FFP processors transform raw materials into ready FFPs, while the wholesaler balances divergent and convergent product and information flows, with the "production" being warehousing with picking and packing (Hübner et al., 2013). Considering this, a further investigation led to the understanding that it is the FFP processor's ability to follow demand that limits the ability to meet fluctuating demand throughout the supply chain, rather than the wholesaler's ability to pick and pack the FFPs. More specifically, it is the sourcing of raw materials (i.e. materials requirements planning (MRP)) and the processing into ready FFPs (i.e. master production scheduling (MPS)). Subsequent to this, the focus was primarily on those PECs influencing the FFP processors' MRP and MPS. However, focusing on RP&C, a parallel focus throughout this PhD study is to identify the PECs pertinent to the wholesaler and the retail stores, relating to the information sharing with FFP processors and order decision-making during RP&C.

Thus, the following first presents findings relating to the FFP processors, and thereafter those relating to wholesaler and retail stores. Detailed analyses and descriptions are provided in Papers #1 and #2.

4.1.1. PLANNING ENVIRONMENT CHARACTERISTICS AT FRESH FOOD PROCESSOR: BEEF, PORK, CHICKEN AND FISH

During the identification of PECs at FFP processors, different mappings were used (e.g. supply chain, product flow and production processes) for each FFP supply chain. Based on this, one combined mapping was created for each meat-type, with an identification of the different PECs and FFP processors. Figure 4-19 depicts this mapping of a Beef processor, with an identification of the pertinent PECs at the related processing stage, the area of impact (MRP and MPS) and the type of PECs (i.e. product, demand, supply and production). For Chicken, Pork and Fish processors, see Appendix D.

Figure 4-19. PECs at Beef processor (Christensen et al., 2020b)

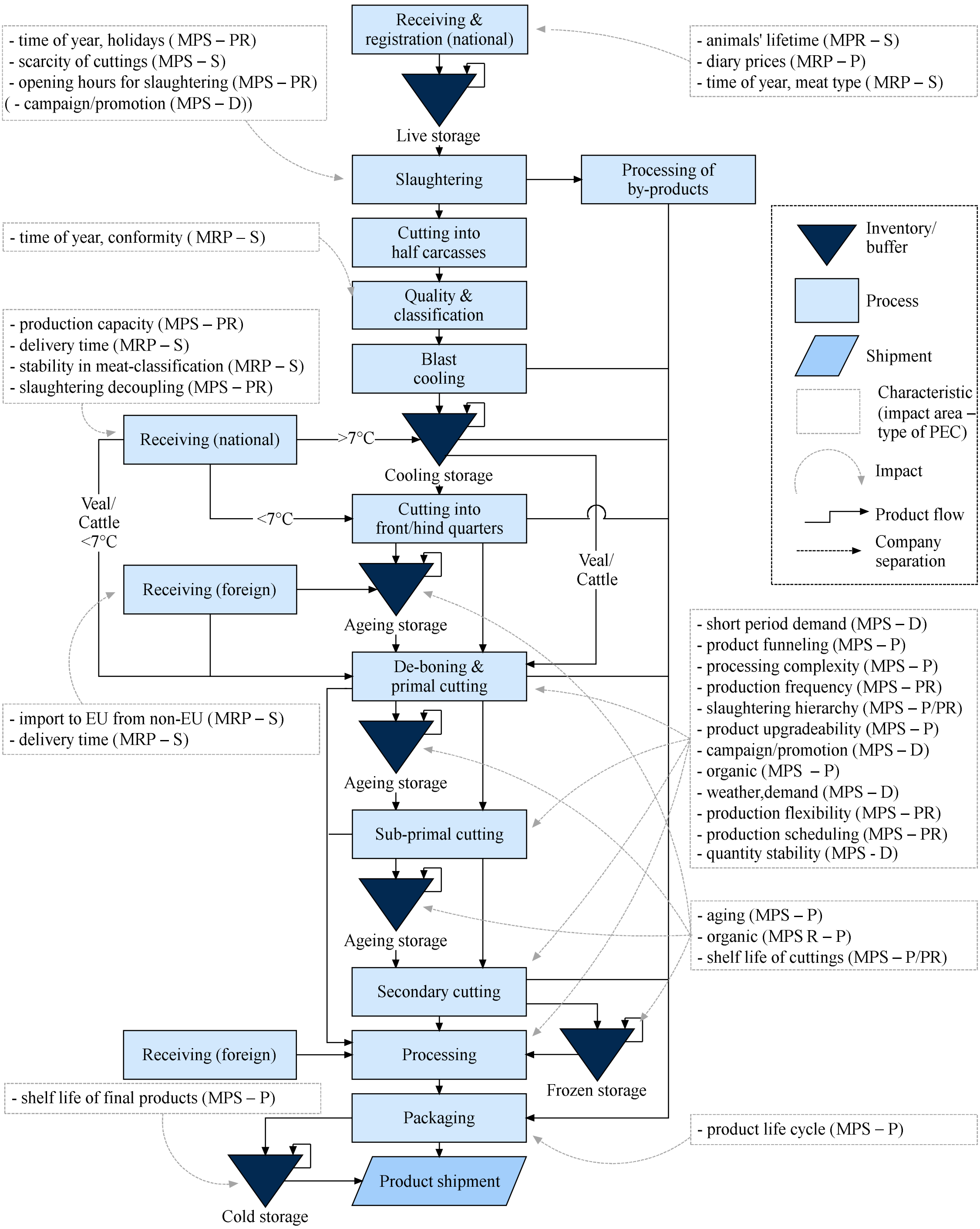


Table 4-11 summarises the identified PECs for all FFP processors and indicates whether the impact is direct (influences the FFP processors) or indirect (influences farmers or fishermen). In total, 29 PECs were identified to have an impact on the information sharing, 28 for Beef, 12 for Fish, 21 for Pork, and 15 for Chicken. A detailed description of the different PECs is provided in Appendix E.

Table 4-11. PECs impacting FFP processor, with identification of relevance per animal type, adapted from (Christensen et al., 2020b)

PEC	Type	Beef	Pork	Chicken	Fish	Impact area
Ageing	P	x				MPS
Animal lifetime/Growth time	S	x	(x)	x	(x)	MRP
Campaign/Promotion	D	x	x	x	x	MRP / MPS
Dairy prices	S	x				MRP
Delivery time	S	x[1]	(x)		x	MRP
Import non-EU to EU	S	x[2]				MRP
Organic	P / S	x[2]	(x)	x		MRP
Opening for slaughtering	PR	x	(x)	x		MPS
Quantity stability	D	x	x	x	x	MPS
(Consecutive) processing capacity	PR	x				MRP
Processing complexity	P	x	x	x		MPS
Processing flexibility	PR	x	x	x	x	MPS
Processing frequency	PR	x	x			MPS
Processing scheduling	PR	x	x	x	x	MPS
Product funnelling	PR	x	(x)	(x)		MPS
Product life cycle	P	x	x	x	x	MRP / MPS
Product upgradeability	P	x	x			MPS
Scarcity of cuttings	P / PR	x	(x)			MPS
Shelf life of cuttings	P / PR	x	(x)	x	x	MPS
Shelf life of final product	P	x	x	x	x	MPS
Short period demand	P	x				MRP
Slaughtering-decoupling	P	x	x			MRP
Slaughtering hierarchy	PR	x	(x)	x		MPS
Stability in (meat-)classification	P / S / PR	x	(x)	x		MRP
Time of year, conformity	P	x	(x)		x	MRP
Time of year, holidays	S / (PR)	x	x	x	x	MPS
Time of year, meat-type	PR	x			x	MRP
Weather, demand	D	x	x	x	x	MPS
Weather, supply	S				x	MRP

[1] = only for imported meat, [2] = only for Beef2

Note: Type: P = product, PR = production, S = supply, D = demand

( ) = indirect impact

The majority of the PECs impact the MPS, and 11 PECs are additional[5] to those identified in the theoretical frame. As an example, "time of year, conformity" relates to the changes in percentage of fat and size of raw materials depending on the time of the year. Consequently, the availability of raw material for a given product may also change, influencing either MRP or MPS. Since e.g. ground beef products are restricted by fat percentage, but per se can be produced from any part of the animal (though at different cost), the change in conformity does not influence the processing, but does the availability of raw material for the product. Thus, it affects the MRP of raw material from farmers to produce ordered amounts. Whereas this PEC directly influences Beef as they source animals and slaughter (thus also conduct quality classification), it influences Pork processors indirectly since they do not slaughter but source pre-specified cuts and pieces.

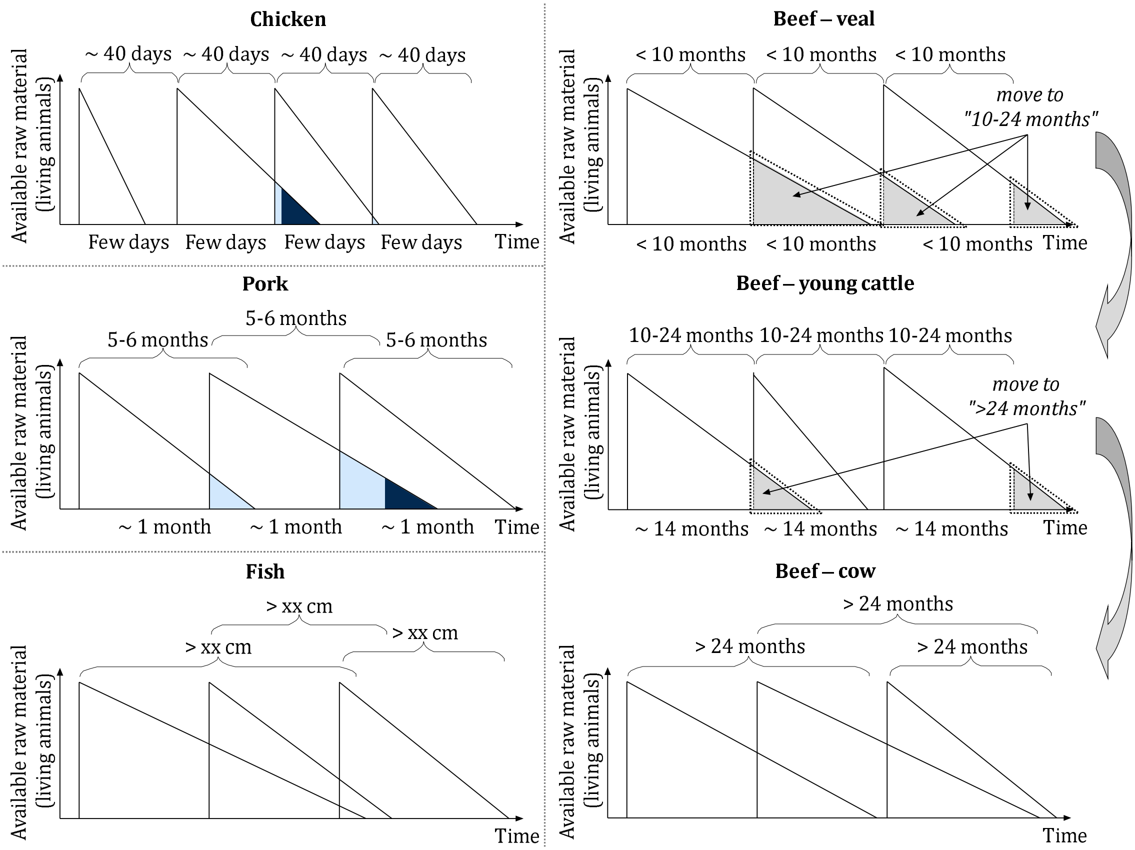
Certain PECs are constant with an identical and consistent impact on processing processes and information sharing, and do not change over time per se, e.g. animal lifetime, availability of meat during the year, ageing periods and scarcities in meat cuts per animal. Other PECs impact changes over time and are less predictable, such as dairy prices, import from non-EU to EU, the weather's impact on supply and production frequency. Naturally, depending on this, information may need to be updated accordingly. As an example, when milk prices paid to farmers increase, the supply of meat decreases (almost) instantly. This entails a need for supplier-driven information sharing when it occurs – and not at scheduled time points. Further, depending on how much the milk prices increase, the impact may differ.

Besides perishability as a fundamental difference to non-perishable items, there are several other PECs found to be unique. An example of a PEC which both differentiates between the product types and is distinguishably different from other perishables such as ready-to-eat meals is animal lifetime (Paper #1). The lifetime of an animal before slaughtering relates to the total supply lead-time. Figure 4-20 illustrates different animals as available raw material upstream in the supply chain (farmer stage) in relation to their lifetime. The y-axis represents the available raw materials for processing at a given time, while the x-axis represents the time. The decreasing line shows the amount of available raw material within the time it takes to breed and grow animals, with an identification of the time period above each triangle. When the demand is larger than expected, the raw material is used (i.e. processed faster) than expected, resulting in out-of-stock since it is not possible to speed up the growth time (as an example, the first cycle for chicken and second cycle for cattle). The light blue areas indicate the excessively available raw material within the maximum time-range during which the animal's lifetime is still acceptable for processing. The dark blue areas indicate the excessive amounts available when lifetime exceeds

[5] Ageing, dairy prices, import non-EU to EU, product upgradeability, stability in meat classification, time of year for meat-type, time of year for meat conformity, weather dependent supply, organic, slaughtering hierarchy and time of year for holidays.

the upper limit for when animals are too old for processing, either due to physical limitations or quality assurance[6]. The grey areas indicate the amounts of excessive raw material which exceed the maximum age limit and thus become unfit for processing, but may be moved further on to a different classification. Thus, the light blue reflects the impact of e.g. over-forecasting, where the excessive amounts can still be absorbed by the following time period's demand, while the dark blue reflects e.g. over-forecasting to the extent that it causes waste upstream.

Figure 4-20. Time continuum for animals' lifetime before the time of slaughtering in relation to different meat types (Christensen et al., 2017a)



In general, three types of time continuums exist, namely limited lifetime, unknown lifetime and "per se" infinite lifetime. While the lifetime of chicken is limited to around 40 days since a longer time may cause their legs to break, the

[6] As an example, chickens' legs may break if exceeding 40 days lifetime as they are not able to carry their bodyweight, and some animals may change taste when growing bigger than a certain size.

lifetime of pigs (i.e. pork meat) is 5–6 months and thus relatively less strict with a time-window of a few months. On the other hand, the lifetime of fish is mostly unknown unless bred in farms (e.g. salmons), as it depends on the size (which is influenced by nature and climate) and area of fishing rather than pre-specified time, following a "the larger, the better" principle. Different from these is beef, where the animals fit different meat-types as they grow, starting with classification as veal and ending as a cow.

4.1.2. PLANNING ENVIRONMENT CHARACTERISTICS AT WHOLESALER AND RETAIL STORES

During the PhD study, several PECs were initially identified and found to have an impact on RP&C at the wholesaler, based on the interviews with the wholesaler and retail stores. Since no PECs were found in the literature specifically relating to the wholesaler and RP&C, the sub-studies evolved on the same frame of PECs as with FFP processors. The identified PECs were described and then compared across case studies in terms of how they are characterised, what their impact is and where they impact. Unique PECs only reported in few retail stores were then excluded, in order to ensure generalisation and compliance with the truth criterion (as discussed in the research paradigm in Section 3.3). Next, the PECs were mapped onto process maps of RP&C, and only those considered relevant to RP&C (and following the scope of the PhD study) were included. This meant that certain PECs having significant influence on e.g. demand forecasting were excluded, since this PhD study delimits demand forecasting to evaluation rather than modelling. As an example, all retail stores reported that the placement of a product in the campaign brochure (front page, mid-pages, back page or in between) and placement in retail stores has a significant influence on the expected demand.

Table 4-12 summarises the PECs pertinent to the wholesaler and retail stores with an identification of type and impact area, i.e. demand forecasting or inventory control. A description of the different PECs is provided in Appendix E.

While five PECs have an impact on demand forecasting (evaluation), all PECs impact inventory control. In particular, substitution demand and inventory, price elasticity and order fill-rate were reported to have a significant impact. While price elasticity is in terms of how much extra demand exists, the order fill-rate is in terms of how much less than ordered is received. However, the two PECs reinforce one another, in the sense that it was reported that in case of a large price reduction, a comparatively large additional demand will occur. Then, if the FFP has a low order fill-rate, an additional amount will be added to the order to ensure product availability. Thus, it should be noted that the more price discounts, the relatively larger quantity is added, causing noise in demand signalling.

Table 4-12. Planning environment characteristics impacting information sharing at the wholesaler and retail stores

PEC	Type	Impact area
Demand type	D	DF , IC
Demand variation	D	DF, IC
Order fill-rate	S	IC
Ordering frequency	D	DF, IC
Price elasticity	D	IC
Shelf life	P	DF, IC
Substitution demand	D	IC
Substitution inventory	PR	IC
Supply lead-time	S	DF, IC

Note: Type: P = product, S = supply, PR = production, D = demand
Impact area: DF = demand forecasting, IC = inventory control

Another two PECs reported to have particular importance on RP&C is substitution demand and substitution inventory. Substitution demand reflects the additional demand from another FFP's out-of-stock situation (demand PEC). If FFP A is out-of-stock it may be substituted with FFP B, causing extraordinary substitution demand of FFP B, and vice versa, depending on the products' positive and/or negative interdependence. The substitution inventory reflects the planned use of one FFPs inventory to cover another FFP's demand. The FFPs have asymmetrical financial losses[7] with an increased food waste focus. Therefore, instead of buying too many FFP Bs (due to e.g. minimum order quantities) which causes excess inventory and increased risk of waste from expiration, the available inventory from substituting FFP A may satisfy FFP B's demand, and thereby mitigate risk.

4.1.3. DISCUSSION

Section 4.1 has thus far presented the empirical findings for the PECs at FFP processor, wholesaler and retail stores. The sub-studies identified 29 PECs pertinent to the four meat-types of FFP processors, of which 18 confirm the PECs already reported in the literature and 11 are new to the current literature. Nine PECs were identified as relevant from a wholesaler and retail store point of view. As discussed in Section 2.2, several studies discuss and refer to PECs, resulting in more than 100 different PECs reported in the literature (see e.g. Jonsson and Mattsson, 2003; Olhager and Rudberg, 2002). However, little attention is given to the impact at a product level (e.g. slaughtering hierarchy and animal lifetime) and whether one PEC which may be relevant to one product is also relevant to another. Indeed, the individual PEC naturally differentiates in its valuation across products, e.g. shelf life is one day for one FFP and four days for another

[7] Too few products cause lost sales, i.e. profit, and thus a fraction of the total product costs. On the other hand, too many products cause price-reduction and/or deterioration, i.e. lost purchase and handling costs, and thus relate to entire product costs.

FFP. However, the underlying reflection and current application of the PEC in planning at product group level still entails an underlying ontological perception that e.g. vegetables are the same as fish. This leads to an understanding that if one PEC is relevant to one product, it must be for all products. Consequently, "all PECs are relevant to all products". Such an understanding impacts both efficiency and effectiveness of RP&C, since it includes PECs which may not even be relevant. The findings point out which PECs are relevant to consider for the different FFPs at the FFP processors, wholesaler and retail stores. Thus, the PECs encompass both at a broader processor level of e.g. processing complexity is pertinent to beef, pork and chicken products, but not fish products. Yet, this is also the case at product level as e.g. scarcity of cuttings for beef products is pertinent to only certain products such as e.g. loin (one per cow/pig) or spareribs (two per pig).

Moreover, the sub-studies provide insight to and evidence of the specific point in the processing where the individual PEC causes an impact on MRP or MPS. The focus in current literature has been on a more general level, e.g. processing complexity is considered in relation to production strategy and thus the extent to which is causes an impact on the (entire) production (e.g. Romsdal et al., 2014). This study expands current knowledge by providing insight on a deeper level for MRP and MPS respectively, considering information sharing during RP&C. It shows that a PEC is per se *not* pertinent to all processing stages, and should thus not automatically (i.e. per se) be included merely due to focusing on production. As an example of beef products, processing complexity is pertinent to the stages concerning de-boning, primal/sub-primal/secondary cutting and further processing, however not to the processing stages such as cutting into half-carcasses and front/hindquarters. At a more holistic level, this study also provides insight into the PECs' pertinence across general supply chain processes as e.g. processing complexity is not pertinent to the sourcing stages (i.e. MRP) in any of the cases. This insight provides a basis for only including those PECs pertinent to a given process, and in turn, increase the effectiveness and efficiency of the research focus.

Further, today, information sharing during RP&C in ARPs govern downstream parties sharing various demand information with upstream parties, with a recent focus on POS data. Although collaborative programs such as CPFR entail mutual sharing, it is done according to scheduled time points and initiated by wholesaler. Certain identified PECs such as import from non-EU to EU and dairy prices impact the MRP at beef processors in the form of ensuring raw materials. This adds to the current understanding of information sharing as certain information must be shared by FFP processors to allow wholesaler to initiate demand information sharing in RP&C. As an example, if approaching the quotas for the import of meat, the wholesaler may need to hedge (within constraints of shelf life) in order to ensure supply for retail stores.

In terms of the PECs pertinent to the wholesaler and retail store levels, this study generally enhances the limited explicit focus on wholesaler (in particular) and retail stores (Fredriksson and Liljestrand, 2015), by enlarging the understanding of which PECs are pertinent. While some of PECs confirm those already mentioned in the literature, other PECs ("substitution inventory," "price elasticity" and "animal lifetime") add to the current understanding. Thus, through the analyses and findings of PECs, the sub-studies related to RQ1a provide a detailed overview of PECs in terms of differences across product types and processing stages. Although for FFP processors different production PECs such as processing capacity and availability of raw material were found to have an impact on the MRP and MPS of the individual FFPs, for wholesaler no *production* PECs (as found in literature) were found pertinent for the individual FFPs for RP&C. Since wholesaler handles entire assortments (i.e. multiple FFPs from different FFP processors) and thus consolidates different product flows, the production-related PECs at wholesaler impact on a general warehouse level rather than the individual FFP. As an example, while (processing) capacity reflects the ability to supply a single product at FFP processor level during RP&C, at wholesaler level (warehousing) capacity reflects the ability to supply any product (from the impacted warehouse).

4.2. INFORMATION SHARING

Information sharing is an integral part of RP&C of FFPs, as it relates to the sharing of demand information across the supply chain, i.e. how many FFPs are needed and when. Information sharing has multiple different facets, and this PhD research study considers six facets, as outlined in Section 2.2: timing, frequency, content, modality, direction and dynamism. Empirical case studies have been undertaken to explore and understand information sharing in FFP grocery retailing.

Three aspects of information sharing turned out to be relevant for understanding how demand information is shared during RP&C of FFPs in grocery retailing. First, the difference between whether the information sharing relates to normal (i.e. all products not sold at reduced campaign price) or campaign sales. Second, the creation and storing (i.e. availability) of the demand information which is shared across the FFP supply chain. And third, the use of demand information during the RP&C of FFPs in grocery retailing. The findings relate to each of these three areas and are thus presented individually in the following, in relation to the information sharing facets. Detailed analyses and descriptions are presented in Papers #2, #3, #4 and #5.

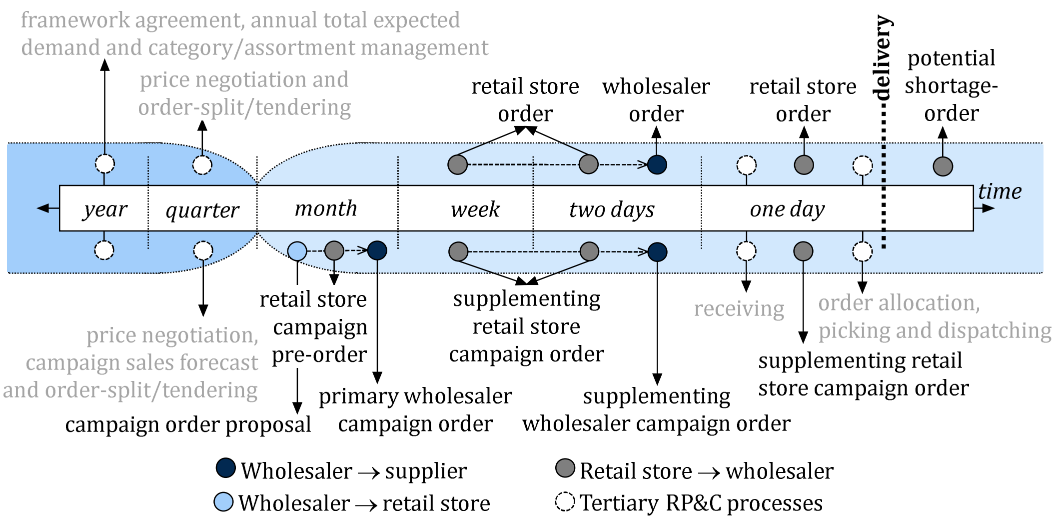
4.2.1. INFORMATION SHARING FOR CAMPAIGN AND NORMAL DEMAND

During the sub-studies, it was found that information sharing during RP&C differs according to demand-type. The demand information is shared with a difference in *timing*, *frequency* and *content* in the supply chain, depending on whether relating to normal or campaign sales. As discussed in Section 3.4, the

RP&C process changed during the PhD research period. At first, the RP&C process was characterised by one cycle with forwarding of actual orders (i.e. cross-docking at wholesaler) and three deliveries to retail stores per week[8], as discussed in Paper #3. Later, the RP&C process changed into two cycles with daily deliveries to all retail stores, as discussed in Paper #5. The following reflects the information sharing in the current RP&C setup.

Figure 4-21 illustrates the time continuum for demand information sharing for FFPs during RP&C, with normal demand-related information above the continuum, and campaign demand-related information below the continuum. The dark blue circles relate to information sharing from wholesaler to FFP processors; the light blue circle relates to information sharing from the wholesaler to retail stores; the grey circles relate to information sharing from the retail stores to wholesaler. Although not directly related to RP&C, to ensure contextual understanding of information sharing in the overall RP&C process, the white circles identify tertiary processes such as annual contractual agreements and FFP receiving, picking and packing. Detailed information about tertiary RP&C processes is provided in Paper #3.

Figure 4-21. Time continuum for demand information sharing during RP&C, adapted from Christensen et al. (2017b)



For normal demand (i.e. FFPs not sold at reduced campaign price), each day (i.e. *frequency*) the wholesaler shares an order covering the total expected demand for the following day (i.e. *content*) with FFP processors (i.e. *direction*). The order is based on a demand forecast and the available inventory at the wholesaler.

[8] Either Monday, Wednesday and Friday, or Tuesday, Thursday and Saturday.

Some retail stores may have already shared their (retail store) order at this time, thus the wholesaler order may be further adjusted accordingly. The wholesaler order is shared one day in advance of delivery from FFP processors to wholesaler and two days in advance of delivery from wholesaler to retail stores[9] (i.e. *timing*). Then, up until noon the day before delivery at retail stores (i.e. *timing*), i.e. the day after the wholesaler order is shared with the FFP processor, the (majority of) retail stores send their order (i.e. *content*) to the wholesaler (i.e. *direction*).

For campaign demand, aggregated forecasts at weekly level (split per supplier) (i.e. *content*) are shared by the wholesaler with FFP processors (i.e. *direction*) up to four months in advance (i.e. *timing*), depending on the size of the campaign (i.e. *dynamism*). The larger the campaign, the longer time in advance. Around six weeks before the campaign starts (i.e. *timing*), the wholesaler sends order proposals to the retail stores (i.e. *direction*). These reflect the wholesaler's expectations of total sales divided by stores and distributed across deliveries (six for a campaign) (i.e. *content*). From the time of receiving the order proposals until five weeks in advance of the campaign period (i.e. *timing*), the retail stores evaluate the proposals, adjust them and send their primary campaign pre-order (i.e. *content*) to the wholesaler (i.e. *direction*). If the retail stores do not change the order proposal, it is considered accepted. Next, the wholesaler aggregates retail store orders and adds a certain percentage according to their own subjective evaluation, expected total demand and experience (i.e. *content*). This is shared with the FFP processor (i.e. *direction*) three to four weeks in advance (i.e. *timing*), depending on the campaign (i.e. *dynamism*). The interviews conducted during the sub-studies revealed that retail stores typically order up to 25% less in their pre-orders than what they order in total for the campaign. The wholesaler accounts for this by manually evaluating total sales and adding a certain percentage based on their own experience, before sharing this with the FFP processor. Then, up until the day before delivery, the retail stores may reduce/increase their pre-order either by notifying the wholesaler (in case of reduction) or sending an additional order (in case of increase) (i.e. *frequency*). The acceptable increase depends on factors such as available raw material at the FFP processor (i.e. max deliverable amount of FFPs). The acceptable range decreases as the deadline approaches. In case the supplementing orders exceed the supplier's capacity or available raw material, the retail store orders are reduced according to received order quantities at the wholesaler.

The information sharing is illustrated in Figure 4-22 from an MRP and MPS point of view, in order to provide a holistic understanding of how the information sharing is characterised, from the point in time when the wholesaler shared order information with the FFP processor (in the figure, day one). The MPS at the wholesaler represents the picking and packing and is only included to ensure a

[9] Some the retail stores may receive the ordered FFPs later on the same day as ordered, due to the logistics setup. However, given the purpose of this study, deliveries are considered to be the following day.

holistic understanding of RP&C across the supply chain. Three separate streams of information sharing are depicted, representing the three types of orders shared for campaign and normal demand. While the dark blue stream reflects the wholesaler order shared with the FFP processor two days before delivery to the retail store, the light blue reflects normal retail store orders shared with the wholesaler, shared the day before delivery (for some stores, the same day) and the grey stream reflects the campaign (pre-)orders shared first between retail stores and the wholesaler, then the wholesaler and FFP processors. In this manner, the retail stores reflect future flows and FFP processors past flows. A detailed description of the flows is provided in Papers #2, #3 and #5.

While for normal demand information sharing occurs immediately before delivery (one day), with the wholesaler providing forecast-based demand information to the FFP processor, this is different for campaign demand, where retail stores commit to an order and share demand information weeks in advance. Further, Figure 4-22 illustrates the product-dependent time of sharing demand information with farmers back in time (for FFP processor), in order to be able to satisfy demand. Depending on the individual FFP, processor plan and release order different time points in advance. In particular for campaign demand, the FFP processor plans raw material orders longer in advance than normal demand, due to the large quantities needed. The effect of this is also reflected in the fill-rate for normal versus campaign demand, where campaign demand entails a higher fill-rate than normal demand (discussed in Paper #3).

Figure 4-23 (from Paper #3) illustrates the fill-rate for normal and campaign orders from FFP processors, given as total per day for one year, where the orders are shared, respectively, the day before delivery (grey) and up to weeks in advance (blue) for four meat-types. Although reflecting a one-cycle RP&C setup, these graphs raise the notion of considering the rather limited collaboration when comparing to the ARPs, both in terms of forecasting and order decision-making. The campaign fill-rates tend to be higher than for normal demand, despite the impact from campaigns' exceptional demand (e.g. the argument for increased collaboration in CPFR (Alftan et al., 2015)).

Figure 4-22. Information sharing during RP&C (Christensen et al., 2020b)

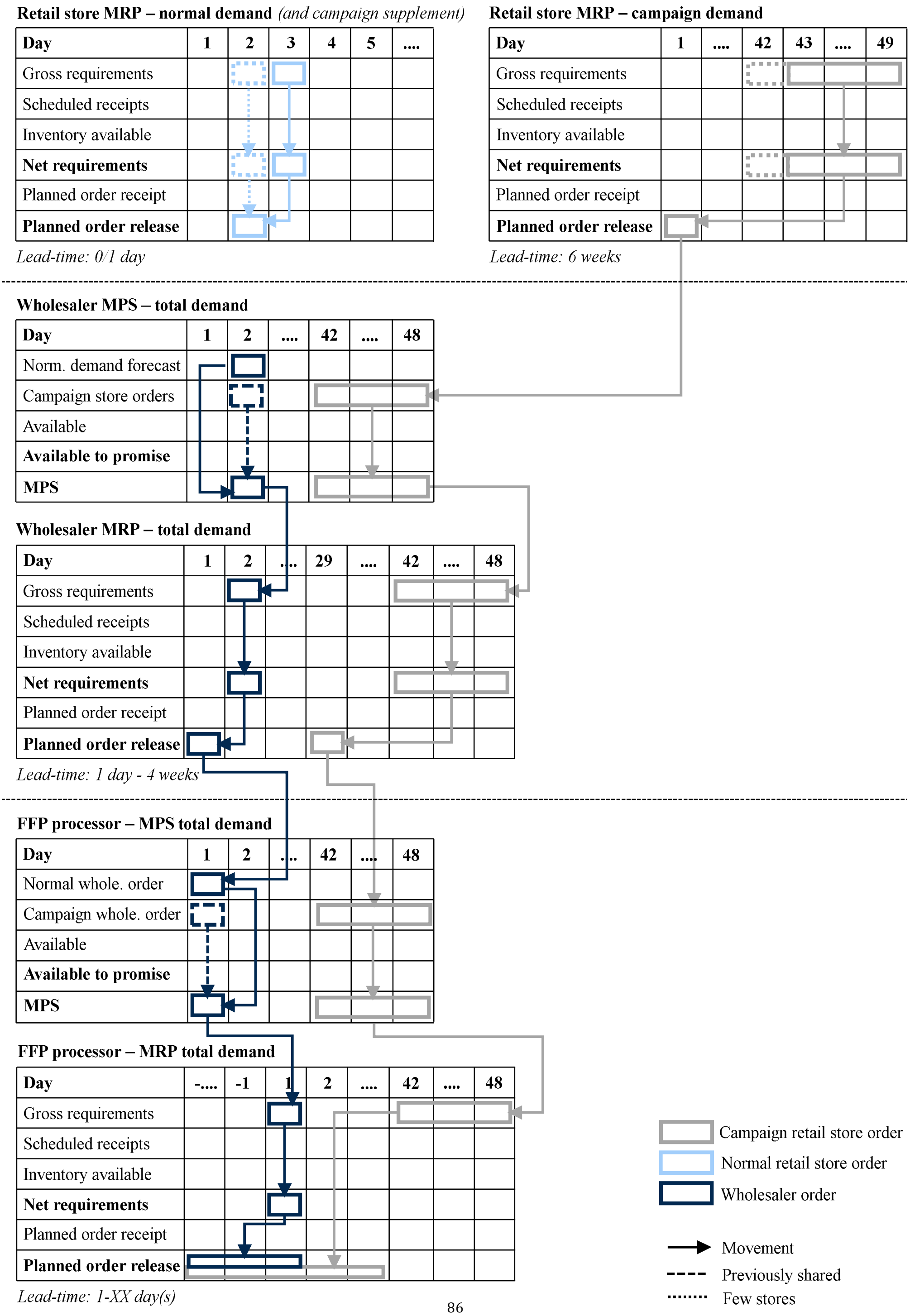
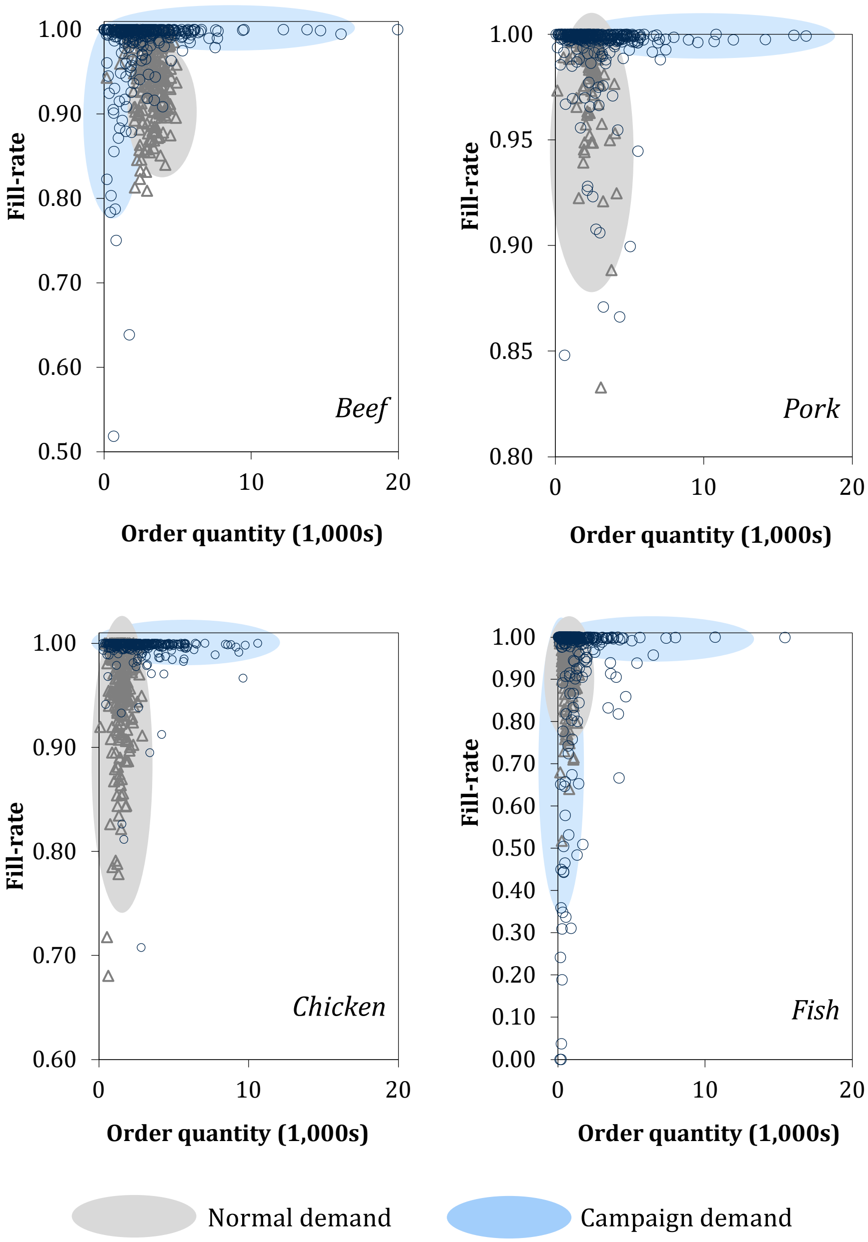


Figure 4-23. Campaign and normal fill-rates versus order size for FFPs (Christensen et al., 2017b)



4.2.2. CREATION AND STORAGE OF (SHARED) DEMAND INFORMATION

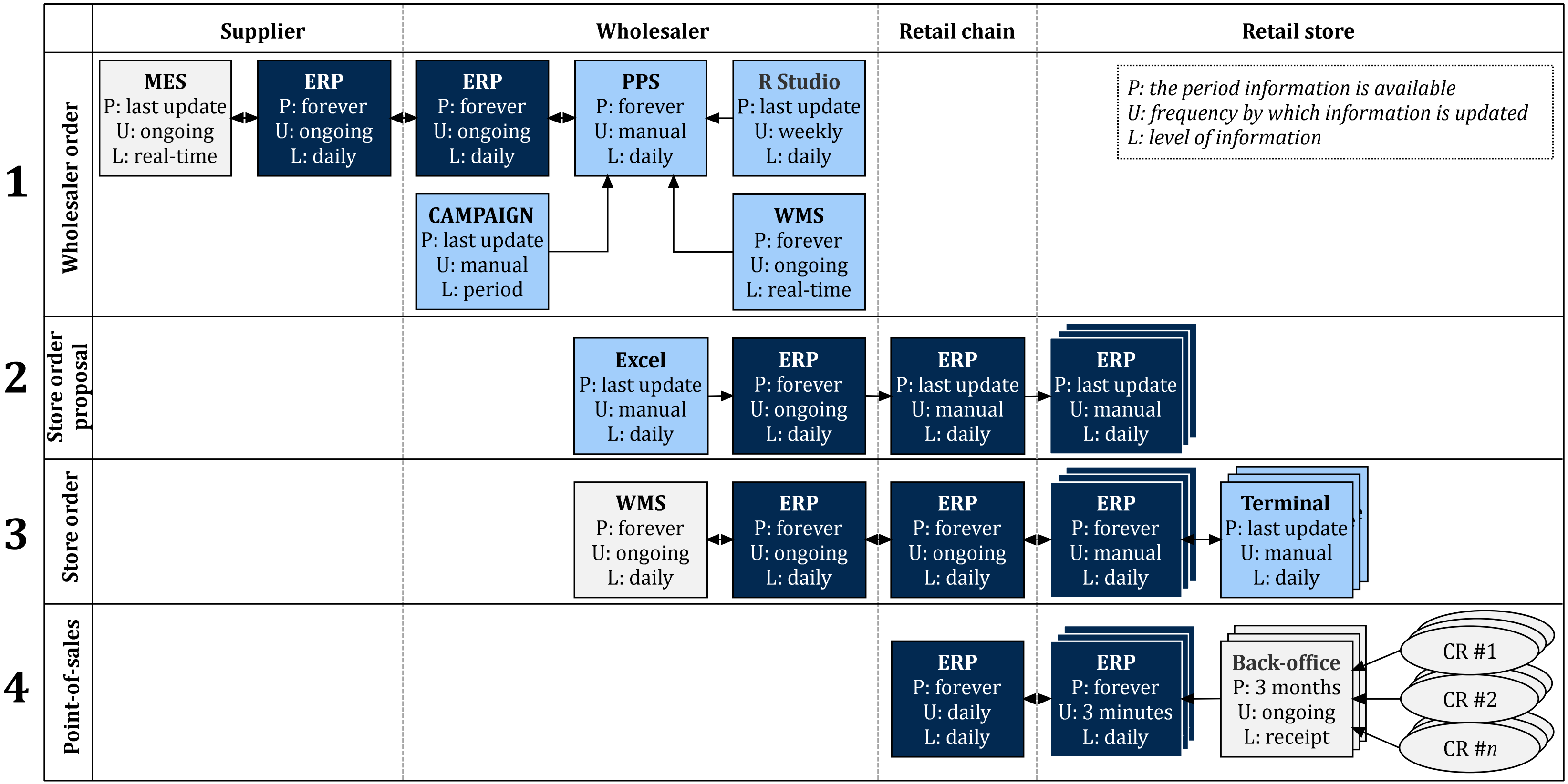
This section presents how the shared demand information is created and where it is stored (i.e. *availability*) across the FFP supply chain. Three main categories of demand information were identified during the sub-studies, i.e. forecasted demand, orders and sales – and for campaign demand, campaign information (i.e. *content*). Although information such as inventory levels at the wholesaler is available, it is not shared. Further, although the retail stores in principle do forecast their future demand of FFPs during their order decision-making, it is subjective and experience-based by the individual person. In this way the creation of demand information from retail stores is a “black box” and thus no systematic derivable in the FFP supply chain is shared.

The demand forecast serves as both the demand-input for order decision-making at wholesaler and information about expected future (campaign) demand at FFP processor. The orders represent forwarded and committed demand of the desired quantities for delivery at the wholesaler (from the FFP processor) and the retail stores (from the wholesaler). The sales represent the actual demand, and while the (historical) retail store orders essentially constitute the demand information used for decision-making at the wholesaler, aggregated POS data is also available and shared by the retail store. For the retail stores, both detailed and aggregated POS data is available. While aggregated POS data is total sale per product per store per day, the detailed POS data includes this information per second.

Figure 4-24 provides an overview of where the shared demand information is created and stored, grouped vertically by supply chain stage and type of demand information (see cycles 1/2/3/4 in the figure). Grey boxes are real-time information systems, light grey are manually initiated systems and the dark blue are ERP systems. As discussed above, the campaign (pre-)orders are shared several weeks in advance of delivery, while normal orders are shared immediately up until delivery.

In cycle one, the wholesaler bases the order on the retail store demand forecast from R Studio, internal information (e.g. inventory level and previous days’ retail store demand) and tacit knowledge about, e.g. the type of campaign, expected competitive marketing and weather (i.e. *content*). The demand forecast itself is a weekly level and then disaggregated to a daily level according to weekday-patterns. After determining the order size according to order-up-to levels for the majority of FFPs (i.e. *timing* and *content*), the order is manually shared with the FFP processor via EDI-FACT (i.e. *modality*) between the wholesaler’s and FFP processor’s ERP systems (i.e. *direction*) daily (i.e. *frequency*).

Figure 4-24. Information creation and storing in systems, adapted from Christensen et al. (2019b)



In cycle two, for campaign demand, the wholesaler bases the order proposal on expected estimates for demand (Excel sheets), historical campaign information from ERP and tacit knowledge (as above) (*i.e. content*). After splitting to store-level (i.e. *timing*), the order proposal is created and shared through the retail chain to the retail stores (i.e. *direction*) via the ERP system (i.e. *modality*).

In cycle three, the retail store order is based on dedicated store personnel's evaluation of available stock and expected demand until next delivery (i.e. following day), following order-up-to level (i.e. *content*). When the order is ready (i.e. *timing*) it is manually transferred from handheld terminals to the retail store's ERP system, then to the retail chain's ERP system and subsequently to the wholesaler 's ERP system. The order is then (after goods receiving) released as a picking-order in the wholesaler's WMS system (i.e. *direction*) daily (i.e. *frequency*). For campaign demand, the order proposal is used as input for the order decision-making in retail stores.

In cycle four, the raw and detailed POS data is recorded at each register in every retail store as sales per second per product, i.e. receipt level (i.e. *content*). It is then aggregated in each retail store's back-office (i.e. *content*) every third minute (i.e. *timing*) every day (i.e. *frequency*), before being transferred to a native database in the ERP-system and further transferred to the retail chain's ERP system around midnight (i.e. *timing*) daily (i.e. *frequency*).

The creation and storing of demand information for sharing is thus characterised as identical for all products, with differences in timing, frequency and modality relating to the individual supply chain stage and cycle, rather than the single FFP. The more downstream, the more detailed the information, the less the storing period of demand information with three months storing of the detailed POS data. Vice versa, when moving upstream the demand information is aggregated and stored forever/until manually updated.

4.2.3. AGE AND TIME-COVERAGE OF SHARED INFORMATION IN THE OVERALL REPLENISHMENT PLANNING AND CONTROL

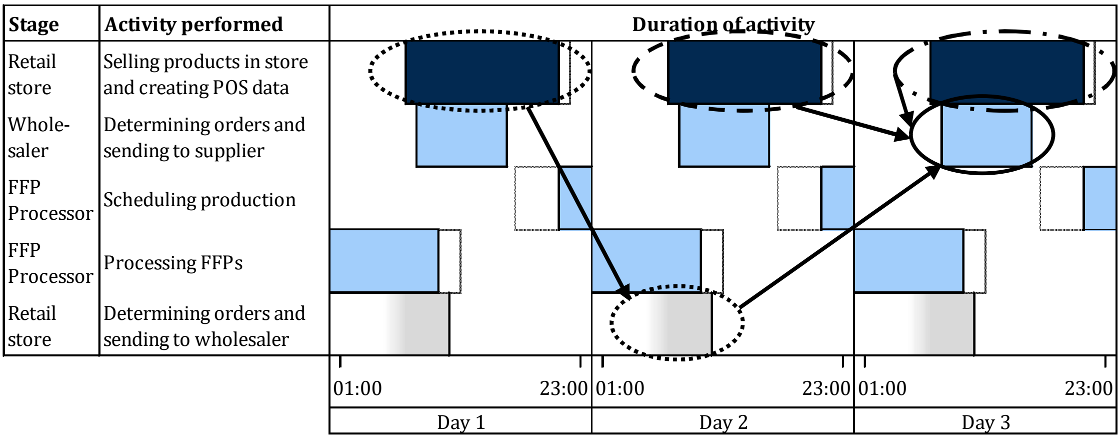
Based on the understanding of how, when and where the (shared) demand information is created as well as for how long it is stored, the following presents the age of the information and the period the demand information reflects. This is placed in the context of RP&C in the FFP supply chain.

Figure 4-25 presents a Gantt chart depicting when the demand information is shared in relation to RP&C and what time the shared demand information represents. The dark blue represents the POS data, light blue the wholesaler order and grey the retail store order, respectively cycle 4, 1 and 3 in Figure 4-24. The circles represent the different demand information and its sequence of creation.

Starting with the creation of the wholesaler order (full circle, day three), the order decision-making and sharing is between 7:30 and 15:30 as standard. The order is based on yesterday's retail store orders (day two), which in turn are based by the stores on the previous day's POS from day one (dotted circles). As discussed previously, the POS data is transferred to the retail chain and wholesaler daily, overnight. During the RP&C cycle, the previous day's POS data is thus available for order decision-making from 07:00 on day two (dashed circle). Although not available to the wholesaler (and remaining supply chain), even newer POS data is created in real-time during the day, i.e. during the order decision-making.

Both content and timing of the information sharing is thus characterised by aggregation (from store to chain), delayed demand signals and uncertainty and noise due to the cumulative interpretation across the supply chain. This is the case, since essentially up to 48 hours old demand information is used when order decision-making occurs at the wholesaler, which impacts the FFP processor's MRP and MPS. More specifically, the wholesaler relies on yesterday's retail orders, which are based on the prior day's sale in retail stores. Although newer information is available, it is rarely used, since this requires manual lookup by the supply chain stages (yesterday' POS data). Real-time is only available in the stores.

Figure 4-25. Gantt chart of demand information flow during RP&C in the FFP supply chain



4.2.4. DISCUSSION

Section 4.2 has thus far presented the empirical findings of information sharing between the FFP processor, wholesaler and retail stores during RP&C. This study has investigated information sharing specifically in terms of six facets, namely content, timing, frequency, modality, direction and dynamism. The focus has been on the difference between campaign and normal demand, the creation and storing of information and the age and time-coverage of information.

The literature on information sharing has generally evolved through two avenues. One avenue, focusing on information sharing as a theoretical and conceptual area between predominantly two supply chain stags has been widely studied (Kembro et al., 2014; Kembro and Näslund, 2014; Kembro and Selviaridis, 2015; Montoya-Torres and Ortiz-Vargas, 2014), although more realistic supply chain constellations are encouraged, e.g. triadic or extended (Huang et al., 2003; Kembro et al., 2014). Recent studies have also focused specifically on the context of perishable products or FFPs, e.g. Lusiantoro et al. (2018) and Nakandala et al. (2017). These studies entail frameworks relating to e.g. the timing and frequency of sharing *or* the content to be shared depending on certain products characteristics, in particular perishability and demand behaviour (e.g. variation and exceptions). Yet, this is without a particular focus on the RP&C process. The second avenue governs the area of ARPs, with a partial focus on different ways of sharing information such as those mentioned in Section 2.1. In this study, the two avenues are combined to verify what is described in the literature empirically and to identify differences between the two (i.e. empiricism and theory) when considering specifically the RP&C process.

One of the main findings relates to the current understanding of the timing and frequency of information sharing in the literature. The design and application of current RP&C frameworks, e.g. CPFR, VMI and ER, rely on the premise of collaboration and more frequent information sharing (see e.g. Hollmann et al., 2015; Pramatari and Miliotis, 2008; Ståhl Elvander et al. 2007). The literature suggests that the level of collaborative decision-making relatively influences a company's performance and that the performance may be further enhanced through high-frequency information sharing and systems integration (Adams et al., 2014; Kache and Seuring, 2014). In particular, e.g. VMI and VOI entail buyer-sharing, and CBMF and CPFR entail (relatively) equal sharing. However studies by e.g. Hartzel and Wood (2017) point out that there is missing empirical evidence regarding the impact of increased information sharing. The results from an analysis in Paper #3 concerning RP&C at the wholesaler indicates that adapting the information sharing according to demand-dynamics, without necessarily increased collaborative decision-making, still yields high service levels. Although not tested, one reason for this may be the timing (one day vs up to four weeks) since this allows FFP processors to e.g. ensure enough raw material for processing (i.e. PECs).

Another finding relates to order decision-making. RP&C in current ARPs entail either supplier/buyer-managed or collaborative decision-making, as indicated in Figures 2-5 and 2-6 (Section 2.1), although collaborative decision-making has characterised the most recent ARPs (CBMF, CPFR, PCSO). Recent studies on order decision-making for perishable/grocery products suggest automatic inventory control where an order is created according to e.g EWA or EWA_{SS} (Broekmeulen and van Donselaar, 2009; Kiil et al., 2018b). There is limited research on RP&C in the franchising context, and only Lee et al. (2016) seem to address this by suggesting a replenishment system with cloud-based computing and artificial intelligence for fuzzy logic in order decision-making. The results from this PhD study provides empirical insight to RP&C about information sharing in the franchising context, specifically information sharing facets and order decision-making.

4.3. DIFFERENTIATED IMPACT ON INFORMATION SHARING

Thus far, RQ1a and 1b have been addressed. More specifically, which PECs relate to RP&C at FFP processors, wholesalers and retail stores – as well as how information sharing is characterised in the FFP supply chain during RP&C. The following synthesises these findings into answering the overall RQ1, relating to how PECs impact information sharing. As discussed above, information sharing should fit the FFP processors given the RP&C and daily processing (i.e. delivery). Given the ongoing creation of POS data (although currently not utilised), Paper #4 reflects the perspective on real-time information sharing and the systemic capabilities from a wholesaler-processor perspective. Real-time information sharing with processing system may improve performance and is possible between production planning and control systems (Mantravadi et al., 2018) Thus, the following considers the options of sharing both historical and real-time demand information, in answering what the impact of PECs on information sharing is and how this differentiates across FFPs. Detailed discussions can be found in Papers #1–#5.

Table 4-13 summarises how PECs impact the information sharing from FFP processors' MRP and MPS points of view. The different PECs are listed with the study design, type of PEC and impact area. Further, there is information about the impact on the different information sharing facets, i.e. requirements. When several options exist, as with e.g. timing (L/D/W/M/Q/Y), this depends on the individual FFP[10]. Some information relating to e.g. ageing, animal lifetime and opening hours for slaughtering is only required to be shared once. In contrast, information affected by e.g. campaign/promotion and import from non-EU to EU must be shared when needed. Other PECs, e.g. meat-type and conformity, require information sharing when they change during the year, i.e. according to dynamism. Thus, depending on the FFP, the information sharing differentiates across PECs.

Further, Table 4-13 also provides information about the level of aggregation. While some information should aggregate according to 'traditional' time-coverage, e.g. daily/weekly/monthly/quarterly/yearly level, other information should aggregate to a PEC-dependent level, such as ageing. As an example, if an

[10] For some Beef products, even whether it is veal, cattle or cow.

FFP is to age for 21 days, the shared information must reflect demand accordingly. Similarly, for production frequency the information should aggregate and comply with the time between production runs.

Moreover, information sharing should not only be from wholesaler to suppliers but also vice versa. As an example, for the PECs "production capacity," "dairy prices" and "production frequency," the supplier must initiate information sharing with the wholesaler. This is so as to ensure the sharing of updated information and reduction of forecasting errors (Christensen et al., 2017a). Given this, information sharing also relates to different planning horizons. As an example for beef products, cows require +2 years animal lifetime and veal <10 months animal lifetime. Thus the information sharing requires both long- and medium-term time horizons – while e.g. chicken with 40 days lifetime relates to short-term.

Figure 4-26 provides an overview of PECs in terms of timing for sharing information and whether the impact is fixed, variable or a mix (i.e. dynamism). While stretched boxes represent the given time a certain characteristic may span over (e.g. delivery time and opening for slaughtering), the separated boxes with arrows show when PECs are meat-type/product-dependent. The white boxes represent the PECs which are fixed in terms of impact on timing, the blue those that are variable and the dark blue those that are a mix, i.e. product-dependent dynamism.

Depending on the product, slaughtering hierarchy and production frequency may be impacted by either no or a certain level of dynamism, i.e. either constant or variable impact. With the frequency of sharing information spanning from real-time to annual information sharing (consequently influencing the aggregation level), it is evident that PECs' impact on information sharing differs across multiple different facets. The majority of PECs entail daily and weekly information sharing, followed by a monthly level. However, PECs representing the specific processing in that of e.g. scheduling, upgradeability, product funnelling and flexibility entail real-time or hourly information sharing.

Table 4-13. Planning environment characteristics' impact on information sharing facets (Christensen et al., 2020b)

PEC	**Literature/Case study**	**Type of characteristic**	**Impacted area**	**Frequency**	**Timing** (sharing of information in advance)	**Direction** (in case of changes to characteristic)	**Modality** (way of sharing)	**Content** (type of information)	**Content** (aggregation of information)	**Content** (planning horizon)	**Dynamism** (variation in impact)
Ageing	C	P / Pr	MPS	O	W/M	W	EDI	F/O	ageing period	S	F
Animal lifetime	L	P	MRP	O	W/M/Q/Y	P	EDI	F	W/M/A	S/M/L	F
Campaign/Promotion	L	D	MRP / MPS	WN	D/W/M	W	EDI	F/O	D/W	S/M	V
Dairy prices	C	S	MRP	UC	W → M	P	EDI	F/O	D/W/M	S/M	V
Delivery time	L	S	MRP	O/ UC[1]	D → M	P	EDI	F/O	transport time / max. storage time	S	F
Import non-EU to EU	C	S	MRP	WN	W → Q	P	EDI	F	W/M	S	V
Organic	(L)C	P	MRP	O	D/W	P	EDI	F	D/W	S	F
Opening for slaughtering	L	Pr	MPS	O	W → Q	P	EDI	F	D/periodically	S	F
Quantity stability	L	D	MPS	O	W → Y	P	EDI	F	--	S	F
(Consecutive) processing capacity	L	S	MRP	O	D/W	P	EDI	F	D/W	S	F
Processing complexity	L	D / Pr	MPS	O	H/D	P	INT/EDI	F/O	time between		
Processing flexibility	L	Pr	MPS	O	R/H/D	P	INT/EDI	O/S	so far/D	E/S	V

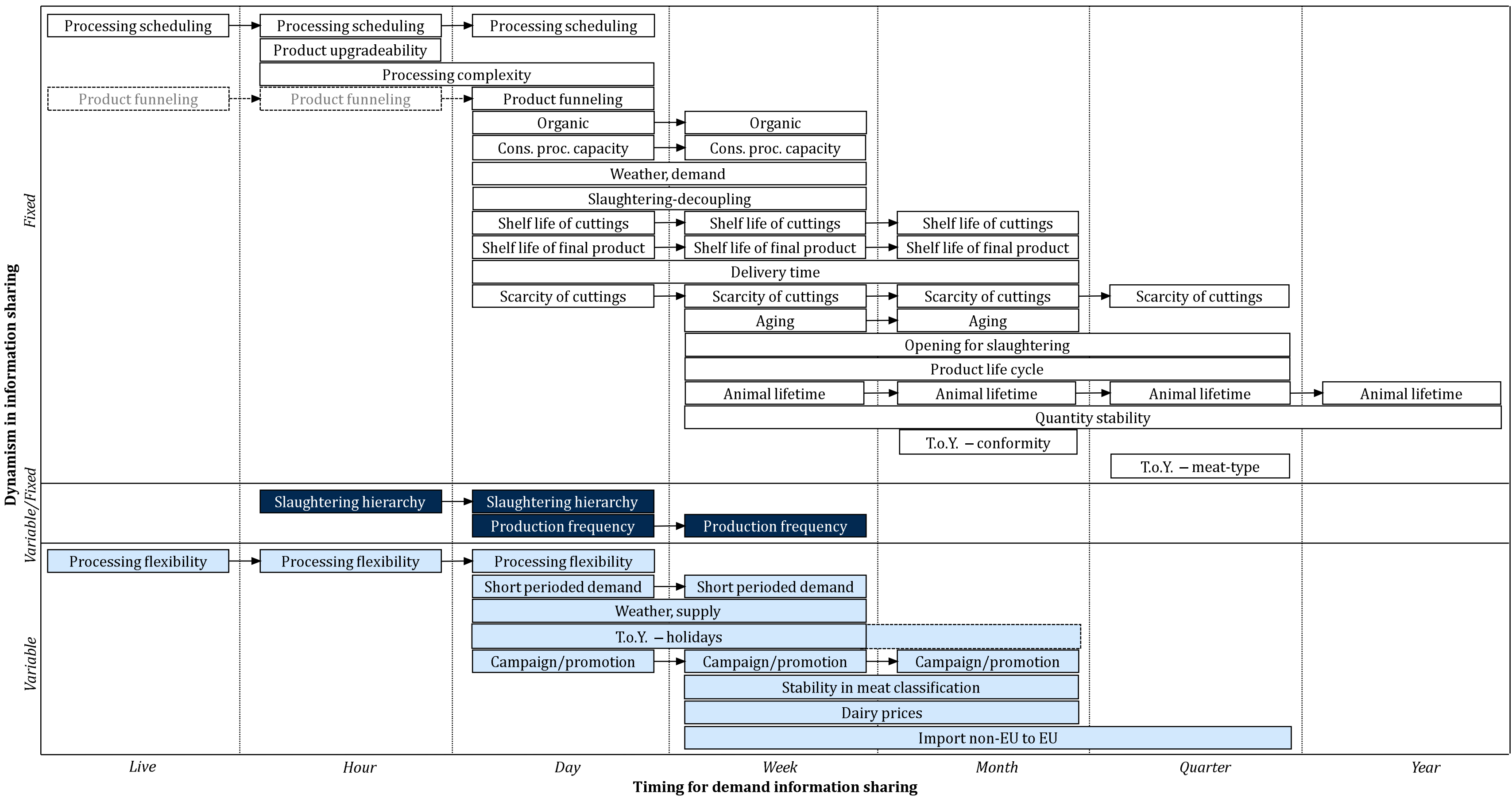
PEC	**Literature/Case study**	**Type of characteristic**	**Impacted area**	**Frequency**	**Timing** (sharing of information in advance)	**Direction** (in case of changes to characteristic)	**Modality** (way of sharing)	**Content** (type of information)	**Content** (aggregation of information)	**Content** (planning horizon)	**Dynamism** (variation in impact)
Processing frequency	L	Pr	MPS	WN	D → W	P	EDI	F/O	demand between processing runs	S	F/V
Processing scheduling	L	Pr	MPS	O	R/H/D	P(W)	INT/EDI	O(/S)	so far/D	E/S	F
Product funnelling	L	P	MPS	O	(R/H)/D	P	INT/EDI	O	so far/D/W/(M)	S	F
Product life cycle	L	P	MRP/MPS	UC	W → Q	W	EDI	F	D/W	S/M	F
Product upgradeability	C	P	MPS	O	H	P	INT	O/S	so far/D	S	F
Scarcity of cuttings	C	P/Pr	MPS	WN	D/W/M/Q	P	EDI	F/O	D/W/M	S	F
Shelf life of cuttings	L	P	MPS	O	D/W/M	P	EDI	F/O	D/W/M	S	F
Shelf life of final product	L	P	MPS	O	D/W/M	P	EDI	F/O	D/W	S	F
Short period demand	L	D	MRP	WN	D/W	W	EDI	F/O	D/W	S	V
Slaughtering-decoupling	L	Pr	MRP	O	D → W	P	EDI	F/O	D/W	S	F
Slaughtering hierarchy	(L) C	Pr	MPS	O	H/D	P	EDI	O/S	D/W	S	F/(V)
Stability in meat classification	C	S	MRP	WN	W → M	P	EDI	F	D/W	S	V
Time of year, conformity	C	S	MRP	UC	M	P	EDI	F	D/W	S	F
Time of year, holidays	(L) C	D/Pr	MPS	A	D → W(M)	P	EDI	F	D	S	V

PEC	**Literature/Case study**	**Type of characteristic**	**Impacted area**	**Frequency**	**Timing** (sharing of information in advance)	**Direction** (in case of changes to characteristic)	**Modality** (way of sharing)	**Content** (type of information)	**Content** (aggregation of information)	**Content** (planning horizon)	**Dynamism** (variation in impact)
Time of year, meat-type	C	S	MRP	UC	Q	P	EDI	F	D/W/M	S	F
Weather, demand	L	D	MPS	WN	D → W	W	INT/ EDI	F/O/S	so far/D/W	S	F
Weather, supply	C	S	MRP	WN	D → W	P	EDI	F/O	D/W	S	V

[1] if transport time fluctuates

Note: Literature/Case study: L = literature, C = case study
Type of PECs: P = product, D = demand, S = supply, Pr = production
Frequency: O = once, A = annually, WN = when needed, UC = upon changes
Timing: R = real-time, H = hour, D = day, W = week, M = month, Q = quarter, Y = year
Direction: W = wholesaler, S = supplier
Modality: EDI = Electronic Data Interchange, INT = internet/real-time tool
Content (type): F = forecast, O = order, S = sale
Content (aggregation): D = daily, W = weekly, M = monthly, A = annually
Content (planning horizon): E = execution, S = short-term, M = medium-term, L = long-term
Dynamism: F = constant (no dynamism), V = variable (dynamism)

Figure 4-26. Timing for demand information sharing when complying with PECs (Christensen et al., 2020b)



4.3.1. DISCUSSION

Based on the different PECs identified in the FFP context and the information sharing during RP&C, Section 4.3. has presented how the 29 identified PECs impact information sharing during RP&C, including what information to share (i.e. content) as well as when (i.e. timing), how often (i.e. frequency), with whom (i.e. direction) and in what way (i.e. modality), as well as whether these are variable, fixed or a mix (i.e. dynamism).

As discussed in Section 2.3., effective information sharing during RP&C of FFPs should be frequent and timely (Lusiantoro et al., 2018; Siddh et al., 2015) and in a systematic manner so as to avoid information overload (Endsley, 2000). Further, information sharing should be based on an "understanding of all the supply chain attributes (i.e. PECs) rather than relying on generalizations" (Nakandala et al., 2017, p. 114), in order for the information to be utilised and integrated into the recipient's process(es) (Jonsson and Myrelid, 2016). However, although the current information sharing frameworks entail earlier (i.e. timing) and more often (i.e. frequency) information sharing, they differentiate at the supplier level or according to demand characteristics (see e.g. Jonsson and Mattsson, 2013).

The findings in Table 4-13 contribute to this by enhancing the understanding of how individual PECs impact information sharing, and subsequently how the information should be characterised accordingly, thereby reducing the overload of information shared in the supply chain. It was found that for some PECs[11] the impact on information sharing is generally due to their very low relation to the product-specific situation. As an example, time of year holiday reflects certain restrictions on national scale (often labour union enforced), e.g. closed on Christmas eve. Although this is obviously country-dependent, it is still imposed on a national scale, and thus has the same impact for FFP processors in the same country – which may be assumed to be due to the short shelf life, i.e. requirements for short distance in transport. For other PECs they only impact information for the FFP processors where the breeding/growth is not controlled by the farmer/FFP processor. As an example of relevancy, weather affects fish processors, since conditions in nature have a direct impact on raw material availability. This is similar for the processing capacity which appears to be relevant when FFP processors experience bottlenecks. Further, it was also found that some PECs are externally enforced and thus the impact on information sharing depends on an external residing event, e.g. increase/reduction in dairy prices and approaching raw material unavailability due to import regulations. These PECs and their impact thus provide a new and nuanced view on how information should be shared. No current study has defined these PECs across different FFPs.

[11] Product life cycle, campaign/promotions, weather demand and shelf life of final product seem to be universal product/demand-related PECs, while time of year holiday, processing scheduling and processing flexibility are not universal.

Further, some PECs such as the conformity of raw material has from a wholesaler perspective previously been understood as supplier-error-related consequences from e.g. a batch of lower quality, and thus considered subject for return/waste for the given FFP. Thus, conformity has unfolded as unavailability (i.e. reduced delivery performance) and been otherwise accounted for by buffering and maintaining inventories in RP&C (when shelf life permits). This PhD study provides a different perspective in that MRP and MPS (thus RP&C) must account for e.g. the conformity of raw material during the year. This is done by adjusting the MRP and MPS through e.g. buffering in case small animals are slaughtered. Hence, instead of wholesaler considering a given FFP as unavailable and subsequently implementing buffers against this in the next order, the orders of other FFPs (where the given raw material may then be suitable) may be adjusted according to the consequent increased availability, as raw material for the other FFPs (following the different levels of cutting and processing complexity).

Reducing the impact of the PECs requires that the FFP processors operate at (inter-) national scale and thus supply other customers. In this manner, the wholesaler may represent only a rather small part of the demand of some FFP processors. Hence, for branded products or products with the same raw material, the wholesaler's order quantity may be so relatively small that in practice it doesn't have any impact. Considering this, some PECs may in fact be less relevant. Although not investigated in this PhD study, this could further entail a differentiation in the inclusion of PECs according to FFP processors' company size or product-customer portfolios.

5

DIFFERENTIATED REPLENISHMENT PLANNING AND CONTROL

The purpose of this chapter is to present and discuss the results and findings related to RQ2. This chapter advances the understanding of how planning environment characteristics (PECs) may be used in effective and differentiated replenishment planning and control (RP&C) for fresh food products (FFPs). The focus is on information sharing and order decision-making, namely the evaluation of demand forecasting and inventory control.

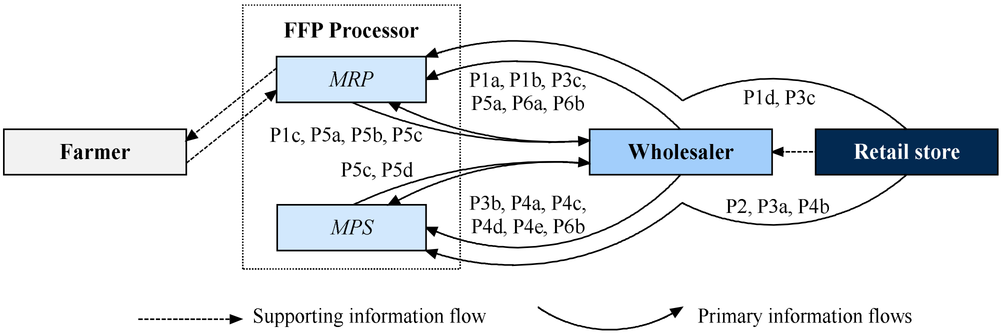
> **RQ2**: How can wholesaler effectively plan and control replenishments according to the fresh food planning environment characteristics, and what is the impact on performance?

This chapter comprises five sections. Section 5.1 presents propositions for differentiated information sharing in the FFP supply chain. Section 5.2 presents the results from a study concerning real-time point-of-sale (POS)-based versus order-based demand information sharing for order decision-making. Section 5.3 considers order decision-making with a method for asymmetrical forecasting evaluation, guidelines for replenishment planning and a multi-product inventory control heuristic. Discussion of the findings is provided in relation to the current stance in the literature as clarified in Section 2.

5.1. PROPOSITIONS FOR DEMAND AND SUPPLY INFORMATION SHARING CONTINGENT ON FRESH FOOD PROCESSORS

Empirically studying the FFP processors' material requirements planning (MRP) and master production scheduling (MPS) as information sharing contingencies during RP&C led to 19 propositions. They entail effective information sharing considering the PECs' impact on the information sharing facets (discussed in Section 4.1). Figure 5-27 depicts which information flows the propositions belong to (full arrows) and the supporting flows (dashed arrows) affecting the primary information flows. Certain propositions are listed twice, as the flow depends on the context. The propositions are grouped into six categories depending on the similarities of the dominating PECs. As an example, in propositions P1a–d, animal lifetime, delivery time and ageing relate to the time it takes to source raw material (i.e. MRP), whether it is from farmers or from maturing/ageing. The following briefly discusses the propositions, while an elaborated presentation of each proposition is provided in Appendix F.

Figure 5-27. Overview of propositions in relation to the demand and supply information flows (Christensen et al., 2020b)



5.1.1. SOURCING OF RAW MATERIAL PROPOSITIONS (P1A–P1D)

Two general supply lead-times were evident: long/short predictable and unknown/stochastic. When the supply lead-time is predictable, the wholesaler would benefit from sharing the demand forecast/order upstream according to the processors' MRP. This timing may be fixed/scheduled. For long supply lead-time, e.g. for beef products, the processor may first plan and forecast demand (cf. farmer breeding animals) and later schedule/place the order in MRP (cf. farmer shipping animals). Thus, wholesaler would benefit from sharing demand forecast or order time in advance, to ensure raw material availability (MRP), with P1c entailing supplier-initiated sharing. When supply lead-time is short, as with e.g. chicken, the forecast may only be shared once, or just an order covering the growth time may be placed.

When the supply lead-time is unknown/stochastic, buffers/inventories are typically built to withstand fluctuations (Chaudhary et al., 2018). Yet, since impacting the quality, minimum storing should be entailed to ensure high quality. Thus, information sharing should be agile so that the wholesaler shares information on demand from the FFP processor as needed. Since information about sourcing options may not be available until the last moment of MRP, and since it is not possible to determine the coverage period, demand information should cover the period until the next delivery. As an example, fish FFPs are characterised by unknown/stochastic supply lead-time and raw materials are delivered to FFP processors the same day as acquired/caught. Hence, the raw material availability is unknown until hours before delivery and processing at

FFP processors. Since information is needed so (relatively) late, the store orders may be available to wholesalers, rather than forecasted demand.

5.1.2. PROCESSING FLEXIBILITY PROPOSITION (P2)

All FFP processors reported different flexibility in the processing of FFPs with few days shelf life, allowing "on-the-go" adjustments of an ongoing processing. This is dependent on planning and scheduling constraints such as available raw material, processing schedule and available capacity (Entrup, 2005; Fleischmann et al., 2015; Romsdal, 2014), as well as the individual FFP, e.g. level of processing complexity, upgradeability and funnelling. This include e.g. certain beef FFPs, which may go through primal, sub-primal, secondary cutting or processing with both varying availability (number of cuts per piece) and value. Consequently, sharing real-time demand information would allow adjusting the MPS and ongoing processing in real-time (Christensen et al., 2019b). This may be the case with e.g. fish FFPs which have particular short shelf life.

5.1.3. WEATHER PROPOSITIONS (P3A–P3C)

Weather impacts the demand and supply and thus MPS and MRP (e.g. Alftan et al. 2015; Taylor and Fearne 2009; Dreyer et al. 2018). Combined with requirements for freshness and availability, this stresses the need for effective information sharing. The demand for some FFPs is e.g. influenced by temperature, and other FFPs by e.g. the amount of sunlight and wind. While cold/warm months are easier to forecast, demand fluctuations due to specific temperature ranges, sunshine and wind are more difficult to manage. As an example, the demand for garlic marinated shrimp in a foil tray for grilling (a BBQ product) increases with sunny and warm weather and decrease with cloudy/rainy weather, in turn influencing the order size and demand per product. Further, the supply of raw materials for fish products is influenced by e.g. strong winds or storms which, in the worst case, can lead to no catch at all. Although fish FFP processors may already account for this in their MRP (and MPS), this seems to be without the most recent demand information, considering wholesalers share orders after FFP processors plan MRP (as discussed in Section 4.2.). Thus, there may be value in timely and frequent information sharing, for both weather-sensitive FFP demand and raw material supply. This is particularly the case since processors source the fish in the morning of the day in which they process them into ready FFPs.

5.1.4. SHELF LIFE AND UNDESIRED AGING PROPOSITIONS (P4A–P4E)

Perishability impacts the MPS at the FFP processor, hence both work-in-process (WIP) and finished FFPs. With total shelf life ranging between weeks and a few days, it dictates the ability of having buffers/inventories for meeting fluctuating demand along the processing (Christensen et al., 2019a). In a similar vein, ageing also dictates the MPS by requiring specified periods of storing before further processing/sale. For longer shelf life FFPs with high demand, it may even be appropriate to maintain stock-levels for meeting fluctuations. Depending on the shelf life, FFPs may be processed more/less frequently. While short shelf life FFPs are processed daily, longer shelf life FFPs are typically processed at planned timepoints and less frequently. Consequently, information sharing should reflect this by ensuring high forecasting accuracy, and for short shelf life FFPs, orders should be updated in cases of changes in demand (particularly if less than expected demand).

5.1.5. ENFORCED SCARCITY/EXCESS PROPOSITIONS (P5A–P5D)

Related to MRP, Beef1 reported quantity restrictions for sourcing raw materials in the EU. When it has a longer raw material/product shelf life, it makes sense to build up inventories of either/both to ensure supply, when quantities are close to not being available. Further, Beef1 reported the effect from changes in dairy prices on raw material availability. Since beef products have both longer and shorter shelf life, there is no per se option for building up inventories in MRP to ensure supply. Further, all processors reported limited processing capacity during specific periods of the year, influencing the MPS. This is when: (1) the demand exceeds the maximum available processing capacity due to campaigns/promotions, slaughtering decoupling and/or (consecutive) processing capacity, or (2) processing capacity is unavailable due to opening hours, processing frequency or closing during holidays. In these situations, it makes sense to build up inventories as part of the MPS to ensure supply. Therefore, sharing both availability information from processors to wholesaler, and thereafter updated order forecasts timely from wholesalers to processors (as event occurs), allows increasing raw material/product availability.

5.1.6. SPECIAL PLANNING ENVIRONMENT CHARACTERISTICS PROPOSITIONS (P6A–P6B)

All processors reported unique product characteristics, requiring additional attention in information sharing. Common to them all is the mix of latent scarcity in availability and supply lead-time. As an example, organic chicken takes a longer time than conventional chicken to grow, and they are typically bred in smaller quantities. This requires earlier information sharing to ensure raw material availability and higher precision in order quantification. Both Beef1 and Beef2 reported that certain FFPs are only demanded during a certain period of the year (alike seasonality). Further, for meat-cuttings with limited availability and subject to product funnelling, freezing is done to ensure having enough supply. Consequently, demand information should be shared a sufficient time in advance, as input to processors' MRP in order to ensure enough raw material.

All FFP processors mentioned the importance of the product life cycle stage and the importance of information sharing when any related changes occur. In the case of the product introduction stage, the service level of the wholesaler (and retail stores) can be affected if demand increases and there is lack of raw material (meat trays, foil, labels, different ingredients/-mixes, etc.). When a product is in the declining stage, the waste level at the processor can increase.

Therefore, the wholesaler should share information upstream about any life cycle changes, according to the material's supply lead-time and/or batch size, enabling improved material/product availability.

5.1.7. DISCUSSION

RP&C in current ARPs reflect the demand so that e.g. the CPFR and CBMF are suggested for exceptions, promotional and campaign demand with (smaller) deviations considering the (intensive) use of resources when creating and evaluating orders and demand forecasts (Alftan et al., 2015; Barratt and Oliveira, 2001; Danese, 2007; VICS, 2010). Conversely, e.g. the VMI is suggested for normal stable demand (Alftan et al., 2015; Ståhl Elvander et al., 2007). Although orders and demand forecasts are shared between FFP processors and wholesaler – depending on the ARP, thus also jointly created – the timing reflects the processing rather than the timing of sourcing the raw materials (Danese, 2007; Thomé et al., 2014; Whipple and Russell, 2007). The demand forecast may be shared from few weeks in advance to one month (Småros, 2007), and be frozen before later turning into committed order(s) or replaced by actual updated order(s) a few days in advance (Alftan et al., 2015; Fang Du et al., 2009; Hollmann et al., 2015; Panahifar et al., 2015). However, most FFPs have a daily demand with higher/lower demand fluctuations due to impacts from e.g. campaign or weather, and the majority of FFPs in an assortment have campaigns on a somewhat regular basis. Since this entails fluctuations in order sizes from wholesaler to FFP processors, sharing information according to MRP and MPS allows FFP processors and wholesaler to synchronise information sharing with retail stores. This allows the supply chain to balance expectations and plans for future demand, while considering e.g. campaign plans and/or raw material availability.

No PEC-specific guidelines are provided in terms of effective information sharing across the supply chain according to FFP processors' MRP and MPS. This PhD study suggests 19 propositions for encompassing the identified 29 PECs. The suggested propositions reflect this across the six information sharing facets while being MRP/MPS-contingent. Thus, the propositions add to the current literature in various ways, presented in terms of information sharing facets, as discussed in the following.

5.1.7.1 Content and Dynamism

Studies suggest that inventory levels and orders are shared with a (static) coverage period, usually time until next delivery, and that it may vary across e.g. context (Kembro et al., 2014), partners (Simatupang and Sridharan, 2005b) and aggregation levels (Watabaji et al., 2016). However, (the most recent versions of) ARPs generally all entail e.g. orders, inventory level and POS data to be shared during RP&C, as discussed in Section 2.3.1. This PhD study expands this current understanding by developing propositions which consider the facets of information sharing on a product level. This is done by finding that some PECs may have an FFP-dependent impact on the coverage period for either MRP or MPS, e.g. animal lifetime (MRP) and ageing (MPS), as well as whether the impact changes through time, thereby entailing different content. Some PECs differ so significantly across FFPs that real-time sharing of retail store demand (i.e. POS data) seems beneficial. In fact, this finding led to a further study on real-time information sharing (discussed in Section 5.2.). Finally, while RP&C in current ARPs entail general and uniform/static information to be shared through time (e.g. a forecast-based order for all products) this PhD study indicates that the closer to processing, the higher requirements for real-time information and product-level differentiation.

5.1.7.2 Timing and Frequency

Studies suggest that the timing and frequency is shared either unscheduled or scheduled (Ding et al., 2014; Ha, Park, and Cho, 2011) at certain time points before replenishment (Kaipia et al., 2017), e.g. when experiencing exceptions or sending an order. However, it is not clear when to choose one over the other, and when to share e.g. real-time information. This PhD study provides propositions for real-time sharing for (weather sensitive) FFPs already in processing or raw materials sourced the same day as processed. It was found that the timing may be on the request from FFP processors (i.e. unscheduled) according to specified rules, e.g. when there is a certain risk for unavailability of raw materials, with maximum/minimum allowed boundaries for deviations. While a static view on information sharing seems to be the case for ARPs, despite the need for timely sharing (Xu, Dong, and Xia, 2015; Simatupang and Sridharan, 2005a), certain PECs entail that varying frequency and timing is beneficial at a product-level, e.g. processing flexibility and time of year for supply (Appendix F). However, although real-time sharing ensures fresh and valid information with reduced uncertainty and noise (Xu, Dong, and Xia, 2015; Chen, Wang, and Yen, 2014), there may be technological barriers for companies given the additional investment into IT equipment and systems to handle and manage the data transfer. Further, when applied to all products it may cause unnecessary use of IT equipment/tools. This is because only a fraction of the assortment requires real-time sharing. Thus, real-time sharing at certain time points may be one option for compromising. Based on this premise, the sub-study in Paper #9 investigated the effect of real-time POS-based information sharing, which is discussed in the next section.

5.1.7.3 Direction and Modality

Studies mainly consider information sharing upstream in serial linkage and information sharing between e.g. FFP processors and wholesaler dependent on the collaboration in the ARP (Alftan et al., 2015; Pramatari and Miliotis, 2008; VICS, 2010). This PhD study found that some PECs entail an FFP processor-initiated demand information sharing. As an example, in the case of enforced scarcity, the FFP processor should initiate the sharing by providing information about e.g. reduced availability or inventory levels. Studies suggests information sharing through a number of different means, and that e.g. EDI leads to a smoother flow given their relatively increased acceptability, ease of use and lower costs (Watabaji et al., 2016). However, it is “critical to determine the specific means of sharing for each piece of information and establish the proper exchange architecture” (Kembro et al., 2014, p. 612), and internet-based sharing tends to be a hyped choice for RP&C in current ARPs (Pramatari and Miliotis, 2008; VICS, 2004; Choi and Sethi, 2010; Marquès et al., 2010). Considering that some ARPs were already suggested in the 1980s and 90s (before the internet was widespread), the later versions seem to have adapted to technological developments and generally all suggest internet-based information sharing across all FFPs, managed through the given ARP. This PhD study found that modality is the least impacted facet of information sharing and only few PECs entail real-time/internet-based sharing. One reason for this was found to be the daily processing due to short shelf life, with for some products entail easily adjustable MPS.

Generally, despite the propositions considering all PECs, it is worth mentioning that information sharing may be impacted by several/all PECs, resulting in different requirements to mainly frequency, timing and content. In this case, it is suggested to evaluate the different propositions in terms of how important they are considered to be and then select down to a few PECs accordingly. This allows grouping FFPs according to their similarities at a still more detailed and effective level than current ARPs.

The propositions also entail that in order to allow FFP processors to be better prepared for demand behaviour, demand information sharing must be relative to e.g. the time it takes to breed and grow the animals until they are ready for slaughtering/catching. In turn, this may influence the performance of the retail stores positively and lead to higher revenue, while also reducing the amount of undesirable noise in the supply chain from premature demand information. Thus, timely sharing of demand information aligns the upstream supply with real demand behaviour. As a consolidator in the supply chain, the wholesaler must be able to interpret and plan according to the expected level of demand (Kuhn and Sternbeck, 2013), “to be more proactive to anticipated demand and more reactive to unanticipated demand” (Lambert, 2008). However, in terms of e.g. animal lifetime, there may be certain implications related to e.g. providing two years or more demand forecast for beef products (cow). One reason is the increased latent uncertainty in the demand forecast due to time horizon and (the required) product level. Combined with this, such time in advance reflects medium- to long-term planning areas rather than RP&C.

5.2. THE EFFECT OF REAL-TIME POS-BASED DEMAND INFORMATION SHARING

The propositions in Section 5.1. are valuable when differentiating information sharing from an FFP processor point of view and considering the MRP and MPS as contingencies to (the facets of) information sharing. While some propositions entail sharing of orders or demand forecasts at e.g. daily or weekly level, other propositions entail a higher frequency, namely hourly or real-time POS data from retail stores (P1d, P2, P3a, P3c and P4b). POS data is often considered the most accurate demand signal for demand/order forecasting (e.g. Williams and Waller, 2010, 2011) and inventory control (e.g. Fransoo and Wouters, 2000). However, as mentioned in Section 2.3, no studies empirically explore the effect of real-time POS-based information sharing during RP&C, i.e. demand forecasting and inventory control combined into one process. Moreover, understanding is missing regarding when it is valuable to share real-time POS-based information over order-based information, considering the demand type and FFP production PECs.

To investigate these aspects, a sub-study (Paper #9) put forth research hypotheses for constructing and testing multiple real-time-based information sharing scenarios across different processing methods and demand types. Due to the focus on information sharing and simplification, processing method was used as an umbrella-classification for the FFPs in order to address production PECs collectively. Considering the wholesaler's point of view of how the FFPs differ, this led to four product-type groups. The FFPs may be whole parts (e.g. whole chicken), cut parts (e.g. steaks or roasts), ground according to specifics (e.g. ground meat) or processed with additional materials in batch-based processing (e.g. marinated meat). The following briefly introduces the specifics of the study followed by a summarised presentation of the effect of real-time POS-based demand information sharing. Detailed discussions are provided in Paper #9.

In total, eight hypotheses were developed to test what the effect of real-time POS-based demand information is on performance and compared to differentiated information sharing. The hypotheses were extended to test across normal and campaign demand as well as whether or not they consider the processing method. It is expected that they will clarify whether real-time POS-based information sharing has a positive or negative effect on performance, i.e. product availability (measured as fill-rate), freshness (measured as inventory days and level) and waste levels (measured as expired products).

For the demand type, it was of particular interest to see the effect for normal and campaign contexts individually, since campaigns heavily influence the grocery industry, and thus product availability (Aastrup and Kotzab, 2010). Since campaign demand has more variation than normal demand, RP&C performance was initially expected to be lower, as there is greater forecasting inaccuracy.

However, since real-time sharing would postpone the timing of demand information sharing, it was hypothesised that performance would improve (Kaipia et al., 2013). Further, since demand for FFPs are affected differently by a campaign, it was assumed that differentiating the manner of sharing information (i.e. either POS or order-based information) at the product level would entail an improvement for both normal and campaign demand. Accordingly, hypotheses H1a, 1b, 2a and 2b were put forth.

> **H1a** During normal demand, real-time POS-based information sharing has a positive effect on performance.
>
> **H1b** During campaign demand, real-time POS-based information sharing has a positive effect on performance

> **H2a** During normal demand, product-differentiated information sharing improves the effect on performance compared to non-differentiated order and real-time POS-based sharing.
>
> **H2b** During campaign demand, product-differentiated information sharing improves the effect on performance compared to non-differentiated order and real-time POS-based sharing.

Despite the recognition of the PECs' (individual) implications for planning, no empirically grounded study provides evidence about the extent to which grouping information sharing according to the differences in processing method impacts the performance. Thus, to consider this, four additional hypotheses are put forth, in order to advance the "individually or all" approach discussed above regarding what the effect of considering the processing method is.

> **H3a** During normal demand, processing-differentiated real-time POS-based information sharing improves the effect on performance compared to non-differentiated order and real-time POS-based sharing.
>
> **H3b** During campaign demand, processing-differentiated real-time POS-based information sharing improves the effect on performance compared to non-differentiated order and real-time POS-based sharing.

> **H4a** During normal demand, processing and product-differentiated information sharing improves the effect on performance compared to non-differentiated order and real-time POS-based sharing.
>
> **H4b** During campaign demand, processing and product-differentiated information sharing improves the effect on performance compared to non-differentiated order and real-time POS-based sharing.

Table 5-14 summarises the hypotheses and indicates the expected relative effect, split across demand type and whether processing method is considered or not.

Table 5-14. Research hypotheses (Paper #9)

	Normal demand	Campaign demand
Not considering processing method	↗ H1a *(real-time)* ↑ H2a *(differentiated)*	↗ H1b *(real-time)* ↑ H2b *(differentiated)*
Considering processing method	↗ H3a *(real-time)* ↑ H4a *(differentiated)*	↗ H3b *(real-time)* ↑ H4b *(differentiated)*

Note: ↗ = positive effect; ↑ = most positive effect

Designed as a multiple case study with six FFP processors, one wholesaler and 329 retail stores, a computation model was developed to test the hypotheses including 50 FFPs and one year of POS data. Details about the method and computation model are presented in Paper #9. Eighteen different scenarios were computed with detailed demand and supply information for two months and 10 additional months for training the used forecasting model. The scenarios reflected order-based information sharing (S2) and real-time POS-based information sharing at hourly intervals of 08:00, 09:00 ... 23:00 (S3a/.../p). In addition, a differentiated approach (S4) was also tested, where the 50 FFPs were split according to best forecasting accuracy[12], as depicted in Table 5-15.

Table 5-15. Number of products per scenario for information sharing in differentiated scenario S4 (Paper #9)

S2 - order	S3a - 08:00	S3b - 09:00	S3c - 10:00	S3d - 11:00	S3e - 12:00	S3f - 13:00	S3g - 14:00	S3h - 15:00	S3i - 16:00	S3j - 17:00	S3k - 18:00	S3l - 19:00	S3m - 20:00	S3n - 21:00	S3o - 22:00	S3p - 23:00
19	*5*	*3*	*4*	*1*	-	-	*2*	*1*	*1*	*2*	*3*	*1*	-	*4*	*1*	*3*

The graphical results for campaign and normal demand are shown in Appendix G and numerical information in Appendix H, while the detailed presentation and discussion for campaign and normal contexts individually are provided in Paper #9. Table 5-16 depicts the summarised results in terms of hypotheses and the effect across the four performance measures and in relation to both S2 (i.e. H1a, 1b, 3a and 3b) and S3a–p (i.e. H2a, 2b, 4a and 4b). While hypotheses H1b, H2a, H3a and H3b were accepted, hypotheses H1a, H2b, H4a and H4b were rejected, since they did not entail improved performance compared to order-based information sharing.

[12] Weighted versions of often used errors in retailing: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Error (ME) (Gneiting, 2011b; Priyadarshi et al., 2019; Ramos et al., 2015).

Table 5-16. Change in performance measures for different scenarios, compared to order-based information sharing (Paper #9)

Demand type	Information sharing	Hypo-thesis	Scenario	Processing method	Fill-rate	Waste	Inventory level	Inventory days	Effect on performance compared to S2	Improved effect on performance compared to S3a/../p	Reject or accept
Normal	Real-time sharing	H1a	nS3	General	↓	↓	↓	↘	*negative*	--	*reject*
		H3a	nS3a/.../p-who	Whole	↓	→	↘/↓	↓	*negative*	--	*accept*
			nS3a/.../p-cut	Cut	↘	↓	→	→	*positive*	--	
			nS3a/.../p-gro	Ground	↓	↑	↑	→	*negative*	--	
			nS3a/.../p-pro	Processed	↓	→/↘	→/↘	↘	*negative*	--	
Normal	Differentiated sharing	H2a	nS4	General	↘	↓	↘	→	*positive*	*positive*	*accept*
		H4a	nS4-who	Whole	↓	→	↘	↘	*negative*	*positive*	*reject*
			nS4-cut	Cut	→	↓	↘	↑	*positive*	*positive*	
			nS4-gro	Ground	↗	↑	↑	→	*negative*	*positive*	
			nS4-pro	Processed	↓	↘	→	→	*negative*	*positive*	
Campaign	Real-time sharing	H1b	cS3	General	↑	↓	↓	↘	*positive*	--	*accept*
		H3b	cS3a/.../p-who	Whole	↑	↓	↓	→/↘/↓	*positive*	--	*accept*
			cS3a/.../p-cut	Cut	↑	↓	↓	↓	*positive*	--	
			cS3a/.../p-gro	Ground	↗/→/↘	↓	↑	↗/→/↘	*positive*	--	
			cS3a/.../p-pro	Processed	↑	↓	↘	↘	*positive*	--	
Campaign	Differentiated sharing	H2b	cS4	General	↑	↓	↓	→	*positive*	*negative*	*reject*
		H4b	cS4-who	Whole	↑	↓	↓	↘	*positive*	*negative*	*reject*
			cS4-cut	Cut	↑	↓	↓	↓	*positive*	*negative*	
			cS4-gro	Ground	↗	↓	↑	↗	*positive*	*positive*	
			cS4-pro	Processed	↑	↓	↘	→	*positive*	*negative*	

Note: ↑ larger increase, ↗ = minor increase, → = no change, ↘ = minor decrease, ↓ = larger decrease in performance

Table 5-17 depicts the results from a sensitivity test that was carried out to investigate how robust the results are, when attaching different levels of importance to fill-rate and waste level in the evaluation. The results are for the different demand types and processing methods, with the best and worst performance. Overall, differentiated sharing (S4) tends to perform best for normal demand, while for campaign demand real-time sharing (S3a/c/e/m/k) performs best, except for ground FFPs where S4 entails the best performance. When waste is most important, order-based sharing entails the best performance for ground FFPs during normal demand. The results indicate that order-based sharing consistently entails the worst performance during campaign demand, regardless of the consideration of processing methods.

Table 5-17. Sensitivity test of performance across demand type and processing method (Paper #9)

Demand type	Processing method	Best scenario performance			Worst scenario performance		
		2*FR + 1*Waste	1*FR + 1*Waste	1*FR + 2*Waste	2*FR + 1*Waste	1*FR + 1*Waste	1*FR + 2*Waste
Normal	-	*S4*	*S2/S3a/S4*	*S3m*	*S3j*	*S3j*	*S3f*
Campaign	-	*S3e*	*S3e*	*S3e*	*S2*	*S2*	*S2*
Normal	Cut	*S4*	*S4*	*S3k*	*S3b*	*S3b*	*S3b*
Campaign	Cut	*S3c*	*S3c*	*S3c*	*S2*	*S2*	*S2*
Normal	Ground	*S4*	*S2/S4*	*S2*	*S3b/m*	*S3m*	*S3m*
Campaign	Ground	*S4*	*S4*	*S4*	*S2*	*S2*	*S2*
Normal	Processed	*S4*	*S4*	*S4*	*S3b*	*S3b*	*S3b*
Campaign	Processed	*S3k*	*S3k*	*S3k*	*S2*	*S2*	*S2*
Normal	Whole	*S4*	*S4*	*S4*	*S3e*	*S3c*	*S3c*
Campaign	Whole	*S3c*	*S3c*	*S3c*	*S2*	*S2*	*S2*

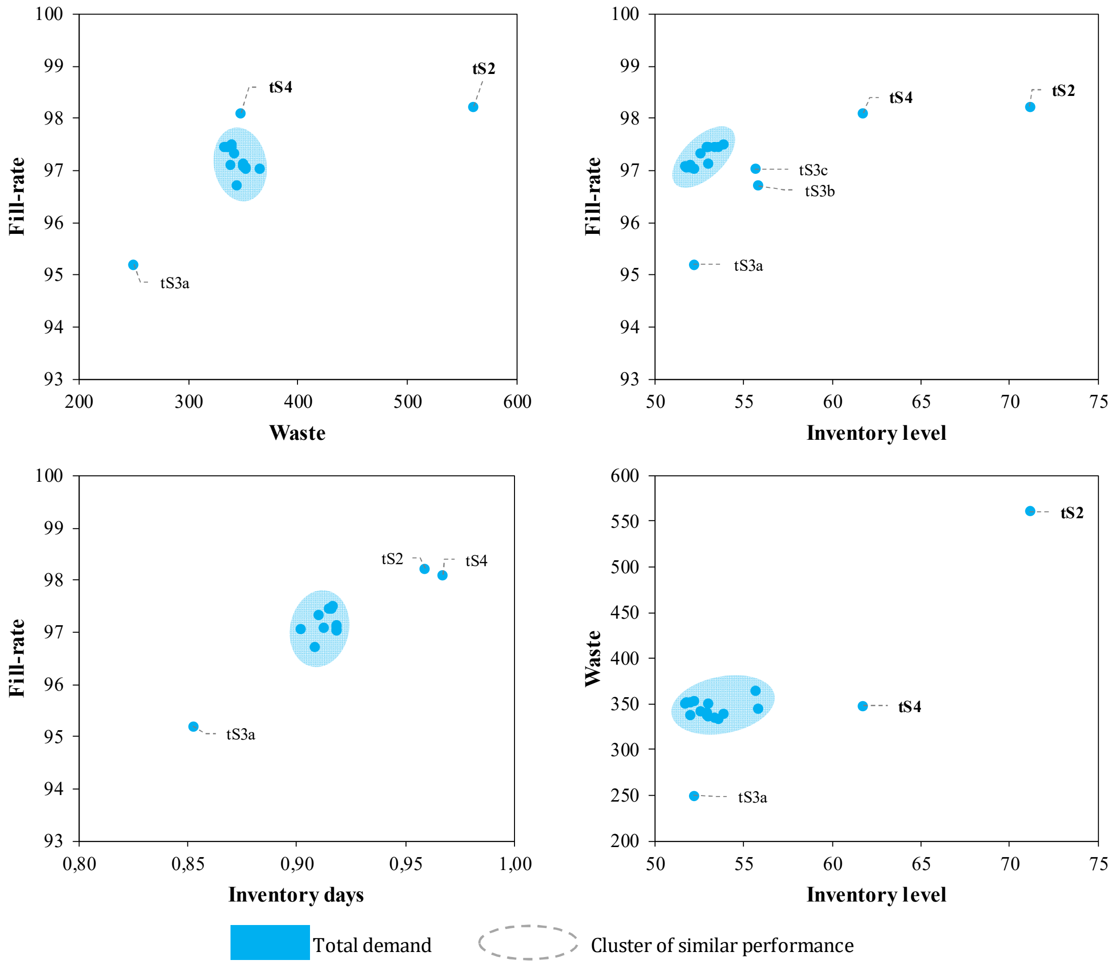
Note: FR = fill-rate, light grey = differentiated sharing, blue = order-based sharing, white = real-time sharing, dark grey= same performance

5.2.1. DISCUSSION

To consider the effect in total, the following first discusses the total performance for normal and campaign demand combined. Figure 5-28 summarises the effect of total order-based (tS2), real-time (tS3a–p) and differentiated (tS4) demand information sharing not considering the processing method.

Starting with the upper left graph, order-based information sharing in total (tS2) entails a 0.1% higher fill-rate than differentiated information sharing (tS4), although a 38% higher waste level. Sharing real-time POS-based information at 08:00 in the morning (tS3a) provides the lowest waste level, yet almost a 3% lower fill-rate. tS4 shows the best trade-off between a lower waste level while retaining a high fill-rate. For inventory level (upper right graph), tS2 results in a 15% higher inventory level than tS4, despite the insignificant difference in fill-rate. Although tS3a–p provide the lowest inventory levels, it is with a lower fill-rate. In relation to inventory days (lower left graph), tS2 and tS4 perform similarly, and since all FFPs have less than one day in inventory, this is not considered any further. Comparing waste to inventory level (lower right graph), tS2 has a significantly higher waste and inventory level compared to all other scenarios.

Figure 5-28. Median performance, total demand

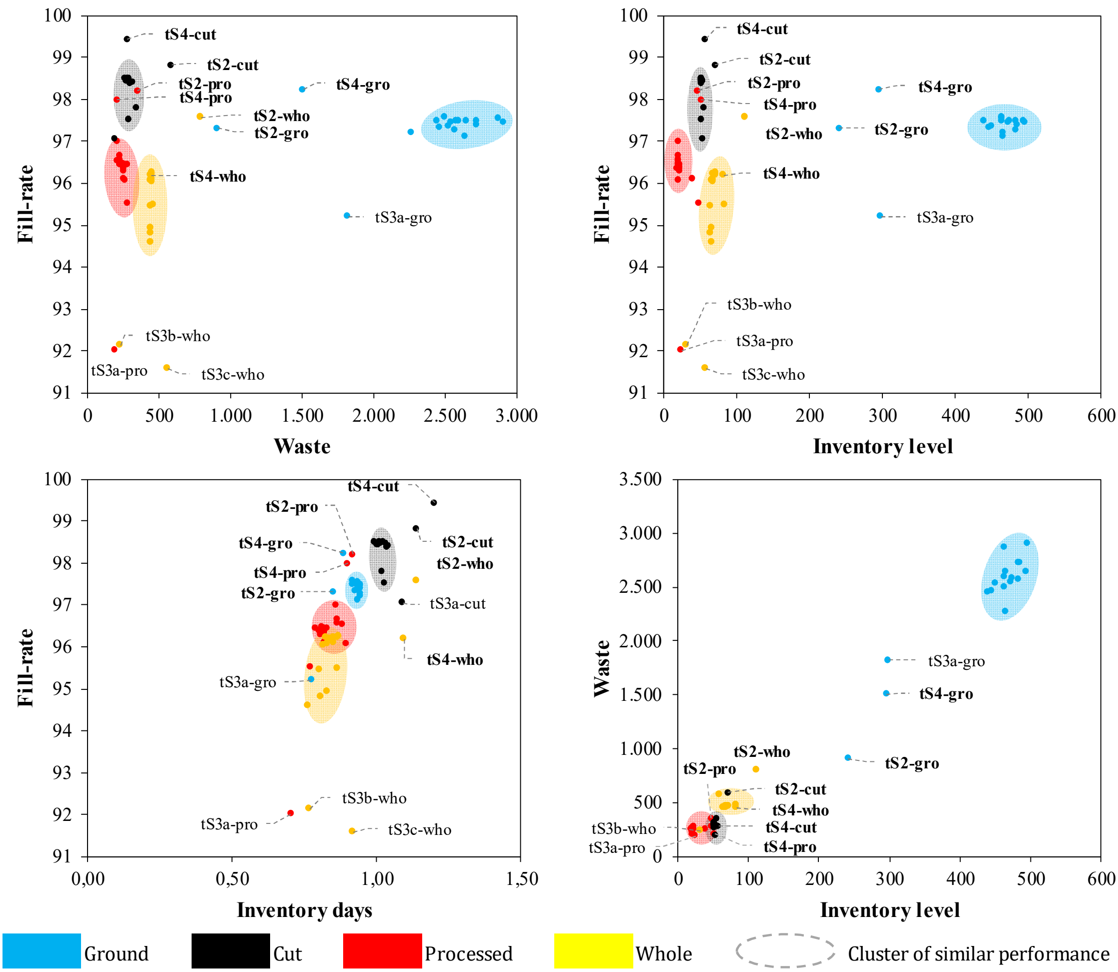


In general, tS3b/.../p perform similarly regardless of the time-point of sharing. This indicates that when considering the demand in total, the specific timing during the day for real-time sharing does not have any significant effect, other than at 08.00 (tS3a). Further, the results show that although real-time sharing (at a single time-point) has the largest negative effect on fill-rate, it has the most positive effect on waste, inventory level and inventory days. From the differences in effect it seems that while tS3a/.../p provides low waste and high freshness, it is at the expense of a low fill-rate. Conversely, while tS2 provides a high fill-rate, it is at the expenses of lower freshness and a higher waste level. The results thus *confirm* that real-time POS-based total demand information sharing has a positive effect on the performance of waste, inventory level and inventory days compared to order-based information sharing. The differences in these aspects are considered to outweigh the up to 1.5% lower fill-rate of tS2 (excluding tS3a). tS4 seems the best trade-off, considering availability versus freshness and waste, resulting in almost the same fill-rate as tS2 but still with a significant reduction in waste and inventory level. This *confirms* that differentiated information sharing improves the effect of real-time POS-based total demand information sharing on performance when considering fill-rate more important.

Figure 5-29 summarises the effect for S2, S3a/.../p and S4, considering processing method. While yellow refers to whole FFPs (the simplest processing method), black refers to cut FFPs, blue to ground FFPs and red to processed FFPs (the most complex processing method). In general, the processing methods create performance clusters, with ground FFPs are the most distinguished.

Starting with the upper left graph, the different processing complexities clearly tend to cluster around similar waste levels, with ground FFPs entailing the highest waste level, up to 10 times larger than the other processing methods. One reason for this could be that ground FFPs generally have shorter shelf life, and are thus more likely to cause waste. Further, ground FFPs have the most flexible processing method with a relatively higher product variety. All processing methods tend to cluster around different fill-rates, with cut having the highest fill-rate and whole the lowest. Specifically, for whole FFPs, order-based information sharing (tS2-who) entails an almost 1.5% higher fill-rate than differentiated (tS4-who), although with 80% more waste. For cut meat FFPs, differentiated sharing (tS4-cut) entails both a higher fill-rate and lower waste than order-based sharing (tS2-cut). For ground meat FFPs, the situation seems to be the opposite, since here differentiated sharing (tS4-gro) has a 0.9% higher fill-rate than order-based sharing (tS2-gro), though 66% more waste. For processed meat FFPs, the difference is the smallest between differentiated sharing (tS4-pro) and order-based sharing (tS2-pro). Ground and whole FFPs have the largest spread in performance. In relation to inventory level (upper right graph), here ground FFPs also perform significantly different than the other processing complexities, with inventory levels up to 25 times higher than the lowest (processed FFPs). Specifically, differentiated sharing for cut and processed FFPs (tS4-cut and tS4-pro) entails lower inventory levels, while for whole and particularly ground FFPs (tS4-who and tS4-gro) this entails a higher inventory level. Pure real-time sharing mostly performs in a range of 100 units in inventory across the whole, cut and processed FFPs. Processed and whole FFPs have the largest deviations in performance. In terms of inventory days (lower left graph), processed and whole meat FFPs tend to perform similarly, with overlapping clusters. All pure real-time scenario clusters have less than one inventory day, except for cut FFPs which have up to 1.3 days. For order-based and differentiated sharing, cut and whole FFPs entail inventory building (i.e. remaining in inventory for more than one day). Moreover, while whole and processed FFPs (i.e. the lowest and highest processing method) entail the lowest fill-rate and inventory days, ground and cut FFPs entail both the highest fill-rate and most inventory days. Comparing waste to inventory level (lower right graph), whole, cut and processed meat FFPs cluster in the same range compared to ground meat FFPs, except for tS4-gro and tS2-gro. Ground FFPs has the largest deviation in performance.

Figure 5-29. Median performance, total demand with processing complexity



In general, tS3a/…/p tend to perform similarly regardless of the time-point of sharing. Hence, regardless of considering campaign/normal demand and processing method, real-time sharing shows no further difference in performance. Further, tS3a/…/p generally have a lower performance regarding fill-rate and inventory level, while having the same waste level and improved inventory days. tS4-cut, tS2-pro, tS2-who and tS4-gro have the best performance, seen collectively.

Although these differences in performance may seem low, when converting them into monetary value it turns out to have a big impact. As an example, for the 50 FFPs included in the sub-study, there was a demand of 6.4 million units in retail store orders during a two-year period. Application of the best performing scenario (i.e. tS4-cut, tS2-pro, tS2-who and tS4-gro) across the 50 products, while assuming current sales prices as well as split between percentage of demand as normal/campaign, would entail an increase in fill-rate from 98.04% to 98.60% in total (i.e. a 29% reduction in out-of-stock situations, from 1.96% to 1.40%) with almost the same waste level. Detailed information is in Table H-13 in Appendix H. Considering the cost savings as revenue in retail stores, this improvement realises extra revenue in retail stores of 2.47 million EUR. Scaling this up to the total assortment with a demand of 15.8 million units, the savings amount to 2.5 million EUR annually in revenue in retail stores.

Both in general (i.e. total demand) and specifically (i.e. campaign and normal demand) did the real-time POS-based demand information sharing for all FFPs at one time-point show a generally positive effect on waste, inventory days and inventory level. While the study showed a positive effect on fill-rate for campaign demand, the computation showed a decrease in fill-rate for normal demand. For total demand the fill-rate also decreased. One reason for this could be the intra-day correlation in demand (i.e. POS data) across the week (Ehrenthal et al., 2014). The weekdays have a same 7-lag demand pattern, where e.g. Mondays tend to have one S-curve, Tuesdays another, etc. Real-time sharing at different time-points throughout the day provides the latest demand signal from the market and "allows to capture the latest demand fluctuations" and "base the order on the actual sales" (Kaipia et al., 2013, p. 272). This improves the expected forecasted demand, and these results implicitly extend the findings from Fransoo and Wouters (2000), whereby POS data (in this case real-time POS-based) has a positive effect on fill-rate and freshness (i.e. inventory days and inventory level) for campaign demand. However, it should be noted that this improvement does not counterbalance the impact of excessive inventory at the end of campaign periods (causing reduced performance particularly due to waste).

Differentiated information sharing with both order-based and real-time POS-based demand information entails the best performance at an overall level. Despite the marginally (!) lower fill-rate (for normal demand), the waste level was largely improved in general. In terms of inventory days and levels, pure real-time sharing entailed better performance sometimes. These results seem to confirm Narayanan et al. (2019) and Williams and Waller (2010) who hold that POS-based forecasting has a positive effect on order-sizing.

In terms of considering processing methods, ground FFPs performed in a manner most different from the other processing methods, which mainly differed in terms of fill-rate. Considering real-time POS-based information with product groupings, the reduced fill-rate – and for ground FFPs waste – did not entail an improved performance, but rather lower performance. However, by grouping according to processing methods, it was found that real-time sharing for cut FFPs with normal demand had a positive effect compared to order-based sharing. This raised a notion regarding the current grouping of products in ARPs (according to demand type): that the consideration of more/other product characteristics may allow a more nuanced understanding of when (real-time) POS-based information sharing is beneficial. Further, considering the PECs reported in the literature, grouping at parallel levels may also provide information about the effect of order-based and real-time information sharing. As an example, grouping according to e.g. demand variation may entail deeper insight into the effect, considering that real-time POS-based information sharing may/may not provide a different picture given the latent increased uncertainty. Moreover, it was interesting that while the product-process matrix from Hayes and Wheelwright (1979) entails lower demand for ground FFPs due to the increased product variation and processing steps, the data indicated that ground FFPs were in fact the products with the largest demand, followed by cut FFPs, and not whole FFPs. Hence, there may be value in including more PECs when deciding on information sharing in real-life.

Overall, the study extends current empirical literature on the effect of POS data on performance (Appendix B) by providing information and results from a holistic point of view on RP&C, combining forecasting and inventory control. Namely, how timing and real-time POS data may improve performance, as well as other performance improvement measures, e.g. waste. Current studies consider either forecasting or inventory control and mainly focus on a week-level decision-horizon, while this study considers a daily level. This study adds to current literature streams on POS data-based information sharing in the supply chain in terms of both inventory/order decision-making (e.g. Croson and Donohue, 2003; Ehrenthal et al., 2014; Williams et al., 2014) and demand forecasting (e.g. Hartzel and Wood, 2017; Jonsson and Mattsson, 2013; Williams and Waller, 2010), both by providing empirical evidence on the context of FFPs and by considering different demand types and processing methods. Specifically, this study also adds to the current conceptual modelling of centralised forecasting (Alftan et al., 2015) by empirically testing the effect of different performance measures. Overall, this study adds to the current literature by being the first study specifically focusing on real-time sharing through a product level scope.

5.3. DIFFERENTIATED ORDER DECISION-MAKING DURING REPLENISHMENT PLANNING AND CONTROL

Apart from information sharing, the second area of this PhD study concerns order decision-making, more specifically demand forecasting and inventory control. The following concerns the results related thereto, by presenting the findings and results from Papers #6, #7 and #8.

5.3.1. EVALUATING DEMAND FORECASTING BY WSLE

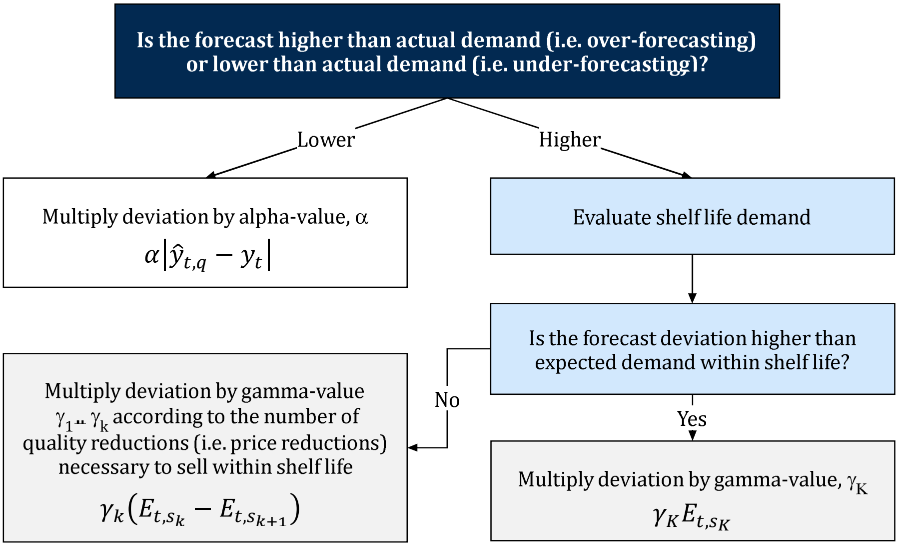
To reflect the impact of FFPs' shelf life when evaluating forecast models, a forecasting accuracy measure which penalises deviations asymmetrically considering the product's shelf life was developed. The measure, weighted Shelf life Error (wSLE), was compared to other accuracy measures such as RMSE, weighted MAPE (wMAPE) and weighted quantile loss (wQL), to evaluate its impact on the inventory (waste potential) and fill-rate (availability).

The wSLE measure departs from a linear deterioration curve (Evans, 2016) which reflects practice well since it entails the same piecewise degradation of the FFP on a daily basis. Depending on the shelf life remaining, FFPs may be sold at full price or with a loss due to (several) price reduction(s) or waste. Inspired by quantile loss, the wSLE splits the penalisation across four types of thresholds:

1) under-forecasting causing reduced availability and lost revenue;
2) over-forecasting where excessive FFPs are sold without a price reduction;
3) over-forecasting where excessive FFPs are sold at a reduced price due to reduced shelf life; the price reduction may happen several times until the FFP eventually expires; and
4) over-forecasting where excessive FFPs cannot be sold within their shelf life, resulting in food waste.

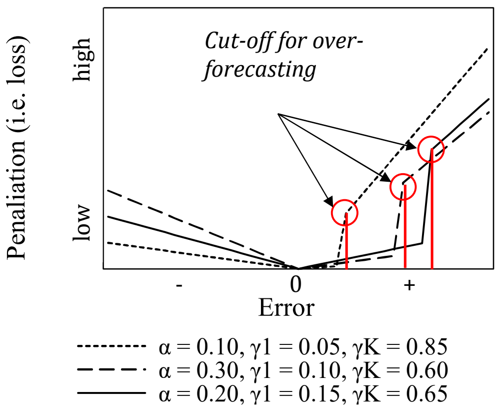
The wSLE measure calculates the deviation's impact relative to its magnitude (scale-independent) and with penalisation according to the decision-process presented in Figure 5-30. By considering the expected demand within shelf life, the wSLE measure evaluates inventory control in the evaluation of forecasting deviations. Depending on which threshold the deviation falls within, an α or γ penalisation value is assigned to the four types of thresholds, respectively. The formulation of the wSLE is presented in Appendix I.

Figure 5-30. Decision diagram for wSLE (Christensen et al., 2020a)



To provide a comparative example of the wSLE (in extension to Figure 2-9 in the theoretical background), Figure 5-31 provides three examples of wSLE with three thresholds. Although under-forecasting is penalised up to three times more than over-forecasting *without* price-reduction/waste, the wSLE considers shelf life's impact on FFPs, where over-forecasting *without* losses is penalised lower than over-forecasting causing losses, and loss from under-forecasting is evaluated relative to loss from over-forecasting (causing expired FFPs).

Figure 5-31. Penalisation symmetry for accuracy measure wSLE considering shelf life, example with three thresholds (Christensen et al., 2020a)



The wSLE was tested on an empirical dataset with 12 months normal demand for 17 FFPs. The average daily demand of the FFPs is between 29 and 602 units, with the maximum allowed day in inventory ranging between one and six days. Specifically, nine FFPs with one storage day, four with two days, three with three days and one with six days is used. The method application involved first generating a rolling one-step-ahead forecast. Quantile forecasts were used and optimised for q={0.80, 0.85, 0.90, 0.95} (Gneiting, 2011a), and seven different forecasting models[13] were included, with each model evaluated according to the four accuracy measures (RMSE, wMAPE, wSLE and wQL). Then, the best performing model for each measure was selected and used in a computation of the inventory level considering an order-up-to approach. The performance of the wSLE was evaluated in terms of fill-rate, waste, lost sales and the resulting inventory as a percentage of demand. Detailed results for the 17 products are provided in Appendix I, and a detailed discussion of the results appears in Paper #6.

In terms of overall impact, the wQL outperforms the other measures by ensuring a consistently higher fill-rate up to 99.27% ($q = 0.95$). However, when comparing wQL to wSLE, the 0.63% higher fill-rate entails 52.6% more waste and 28.6% higher average inventory level ($q = 0.95$). In fact, for all q wSLE entailed the lowest number of excessive FFPs while wQL entailed the highest. Further, wQL also increased the most in excessive inventory across the quantiles. At an overall level, this confirmed the trade-off in penalisation between having a high fill-rate (as in wQL) and ensuring low waste (as in wSLE). Both at product and aggregated level the wSLE consistently performed better in terms of waste, and wQL in terms of fill-rate. Although this is not surprising (thinking of the different penalisations), the wSLE offers a new way of evaluating both the forecasting inaccuracy and inventory when considering waste.

At product level, the study showed that the same forecasting model may be suggested for different accuracy measures. Interestingly, the wSLE is the only accuracy measure differentiating in suggested forecasting models for q = {0.80, 0.85, 0.90, 0.95}, with two/three different forecasting models for 10 out of the 17 FFPs. While the RMSE and wMAPE per se do not select a quantile-specific forecasting model, since they use squared/absolute penalisation, wQL does. However, that the wSLE (and not the wQL) differentiates in actual selection of forecasting models can be attained that while the wQL searches for accurate estimation of point forecasting according to lowest cost (not taking into account the possibility of waste), the wSLE considers the level of waste.

[13] The seven forecasting models range from simple naïve, naïve with seasonality and moving average (Hanke and Wichern, 2009), to more complex models such as ARIMA (Hyndman and Khandakar, 2008), theta (Assimakopoulos and Nikolopoulos, 2000), ETS (Hyndman et al., 2008), and a combination model considering the arithmetic mean value from ARIMA, theta and ETS.

5.3.2. INVENTORY CONTROL GUIDELINES AND EWA$_{3SL}$

With offset from four dominant PECs, a set of four-dimensional guidelines were proposed for the planning of replenishments. Each characteristic is divided into up to three groups (low/short, medium or long/high), and represented in combination with the suggested conceptual model for planning demand and supply of fresh meat products (see Table 5-18).

While FFP demand with a high coefficient of variation entails a more inaccurate forecast and thus requires more attention to the order decision-making, a low coefficient of variation entails high reliability in forecasting and thus less attention is required. In this manner, the lower the valuation the greater the potential for using automated replenishment. While FFPs with a long supply lead-time entail a higher uncertainty in RP&C and a bigger impact on quality degradation of the products (due to relatively higher inventory levels), short lead-time entails less uncertainty in RP&C and less influence on quality level, making these products' replenishment very flexible. While fast degrading FFPs entail more attention and a greater trade-off between cost and quality, lower levels allow for less requirements from management. The lower the degrading speed, the more tolerance for economic order quantity-based management. Finally, while a high order frequency entails that FFPs have a very frequent demand and thus less impact from deterioration, a lower frequency entails greater attention to forecasting and planning. If a product has high frequency (is ordered often), inventories are influenced through lower levels and thus lower risk of obsolescence.

Table 5-18. Replenishment guidelines for FFPs considering four PECs (Christensen et al., 2017c)

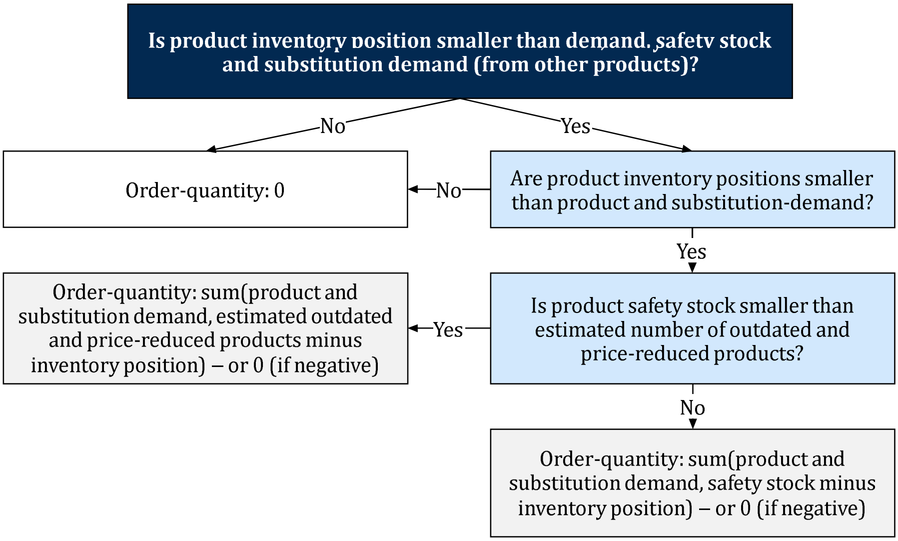
	low	**medium**	**high**
Coefficient of variation	The FFP has stable and predictable demand, where reliable forecast is possible. Little attention is needed for forecast, and the FFP is subject for possible automation. Relatively lower SS and ROP is required.	The FFP has less stable demand and less reliable forecast with significant forecast errors. Forecast requires post-evaluation with possible adjustments. Depending on variation, ROP and SS need periodic re-evaluation.	The FFP has instable demand, significant fluctuations and unreliable forecast with very significant errors. Forecast requires significant attention and constant monitoring of demand. Manage FFPs, SS and ROP closely and adjust accordingly.
	slow	**medium**	**fast**
Degrading speed	The FFP has long shelf life up to several days, even weeks. When ordering use EOQ-based order size calculation.	The FFP has mixed shelf life ranging from few to several days. When ordering use either quality or EOQ-based order size calculation.	The FFP has short shelf life up to only few days. When ordering use quality-based order size calculation, and manage and monitor inventory level closely.

	high	medium	low
Order frequency	The FFP is ordered very frequently (if not each day) and has relatively lower risk for long storage. Given a higher turnover, less attention is needed and the FFP may be subject to automatic order generation (or automatic replenishment).	The FFP is ordered infrequently and is possibly a cyclical product. Manage and monitor products closely, analyse and understand demand and periodically adjust SS and ROP.	The product is ordered rarely (possibly seasonal), has lower turnover and thus faces a relatively higher risk of long storage time. Manage and monitor products closely, analyse and understand demand and adjust SS and ROP accordingly.
	short	**medium**	**long**
Supply lead-time	The FFP has short supply lead-time with fast response time from supplier and thus relatively lower latent uncertainty. Forecast daily and initiate replenishments accordingly. Send forecasts to internal operations and supplier.	The FFP has medium supply lead-time with medium response time from supplier and relatively higher latent uncertainty. Initiate replenishments on daily basis as needed, and forecast medium-term sales with regular review and adjustment. Forecast may be input to medium-term other planning aspects and may thus be forwarded internally and externally (in case of campaigns).	The FFP has long supply lead-time with low response time from supplier and thus high latent uncertainty. Initiate replenishments on daily basis as needed, and forecast long-term sales, with frequent review and adjustment, with principle of general overestimation (due to life-time window). Forecast may be input to other medium/long-term planning aspects and may this be forwarded internally.

Note: SS = safety stock, ROP = re-order point, EOQ = economic order quantity

To reflect the consumer requirements (availability and freshness), impact from substitution as well as mitigation of risk of causing quality reduction and food waste, a multi-product inventory policy was developed, namely EWA_{3SL}. The EWA_{3SL} includes supplier fill-rate, price reduction and substitution and ensures the size of safety stock relative to outdated products by building on the EWA_{SS} (Kiil et al., 2018b). The EWA_{3SL} considers the substitution effect when evaluating relative to available inventory. Moreover, that the substitution of FFP A and FFP B may not necessarily be one-to-one, i.e. equal interdependence. As an example, while a substitute for 8–12% ground beef may be 4–7% ground beef, the substitute for 4–7% may be a completely different product, i.e. thus not necessarily symmetrical demand-effect. As with both EWA and EWA_{SS} policies (Broekmeulen and van Donselaar, 2009; Kiil et al., 2018b), a fixed review period is entailed. This fits with the grocery industry and wholesaler/retail stores placing orders at specified time points regardless of demand type (normal or campaign demand). Having a safety stock for perishable items means a chance for reducing sales price of the product to adjust the inventory position so that waste is avoided. The 3SL in EWA_{3SL} relates to supplier (S), shelf life (SL) and substitution (S). It follows the logic as depicted in Figure 5-32, where one of three different order-sizing decisions applies. The formulation of EWA_{3SL} is presented in Appendix J.

Figure 5-32. Decision diagram for $EWA3_{SL}$ (Christensen et al., 2020)



5.3.3. DISCUSSION

For differentiated order decision-making, this PhD study developed both a new forecasting accuracy measure (Paper #6) and guidelines for inventory control of FFPs (Paper #7), including a multi-product heuristic for inventory control (Paper #8).

Starting with the forecasting accuracy measure, multiple measures are suggested in the literature for evaluating forecasts in the retail context, mainly applying a symmetrical consideration of over and under-forecasting (Huber et al., 2017; Priyadarshi et al., 2019; Van Donselaar et al., 2016). Although the asymmetrical wQL focuses on attaining a high fill-rate (Gneiting, 2011a), it is at the expense of excessive amounts and an increase in inventory levels. The suggested wSLE in the sub-study focuses on ensuring a low level of waste at the expense of rather under-forecasting, while only penalising the absorbable excessive number of FFPs very little. In terms of shelf life, this means that while the wSLE ensures a higher level of freshness, the wQL results in the highest number of days in inventory, i.e. lowest freshness. For more than half of the FFPs tested, the wSLE entailed the lowest number of FFPs being sold at a reduced price, hence ensuring the freshest FFPs. Although the wSLE sometimes selects the same forecasting models as other accuracy measures, the sub-study showed that the wSLE is the only accuracy measure that consistently results in the lowest waste and inventory levels. Despite the fact that the wQL has higher performance in fill-rate, it causes relatively more waste, indicating a non-proportional development in the performance.

A sensitivity test was carried out to investigate how different the performance is when adjusting the penalisation for either over or under-forecasting by +/-20%. From this test, the wSLE consistently selects the forecasting model entailing the lowest excessive amounts (i.e. waste). As expected, when increasing the penalisation for over-forecasting or decreasing the penalisation for under-forecasting (i.e. emphasising waste), lower inventory levels are obtained although higher lost sales. Vice versa, when decreasing the penalisation for over-forecasting or increasing the penalisation for under-forecasting (i.e. emphasising availability), higher inventory levels are obtained although lower lost sales. By focusing on waste and penalising over-forecasting which causes waste, fewer FFPs are sold on discount due to lower inventory levels, i.e. increased freshness. Although the results indicate only a little percentwise change in performance, it is important to keep in mind that the sub-study only includes 17 FFPs. If deploying the wSLE across an entire assortment (with up to hundreds of FFPs), the impact is considered much larger.

Although not tested on empirical data, the EWA_{3SL} allows evaluation according to product characteristics, reflecting the real-life situations even more, in turn resulting in effective decision-making when order-sizing. Thus, e.g. the impact from different rounds of price-reduction on the product demand, is considered. The EWA_{3SL} is expected to bring even lower waste and improved availability than previous results by supporting the mitigation of risks across products.

The two sub-studies concerning the wSLE (Paper #6) and EWA_{3SL} (Paper #8) entail a product-level approach. As an example, the wSLE tests the impact across 17 FFP-specific penalisation at a product level. This is similar for the EWA_{3SL} entailing e.g. a product specific substitution factor for both demand and inventory. However, the values/factors may also be set at group level, e.g. according to animal type or customer groups. In this way the penalisation in the wSLE may reflect e.g. different managerial dispositions as to how waste (i.e. over-forecasting) should be penalised compared to fill-rate (i.e. under-forecasting). Further, by applying the penalisation at product-group level, implications in determining three (or more) penalisation values are also reduced. For the EWA_{3SL}, the group level application may entail ease in deriving the factors related to substitution, although factors such as fill-rate are suggested to remain at a product level due to ‘easy’ derivability.

6

CONCLUSION AND FUTURE RESEARCH

This chapter concludes the research study by revisiting and providing an answer to raised research questions, outlining the theoretical contributions and implications for theory and practice. Furthermore, it elaborates the limitations of the study, and outlines proposals for future work.

6.1. REVISITING THE RESEARCH OBJECTIVE AND QUESTIONS

Several collaborative programs have emerged during the past decades for planning and controlling replenishments in grocery retailing industry. However, apart from entailing heavy use of resources in order to be implemented, the programs entail a "one-fit-all"-approach according to only specific demand characterisations and specify merely an overall frame for collaboration without looking into specifics of information sharing and order decision making while replenishing. A situation which does not encompass that fresh food products (FFPs) are different from one another in terms of e.g. shelf life, time to produce and process and raw material availability. This raised the need for in-depth understanding of how these product differences (expressed as planning environment characteristics (PECs)) affect the replenishment planning and control (RP&C), to the extent that FFPs which are similar across selective PECs are planned and controlled in the same manner.

> **Objective:** The objective is to contribute to how the planning environment characteristics may be reflected in the design of effective replenishment planning and control, i.e. order decision-making and information sharing. Effectivity relates to high availability and freshness with low waste and inventory.

The objective has been examined through two primary questions: the exploratory RQ1 which investigates PECs' impact on information sharing during effective RP&C and the normative RQ2 which suggests methods for effective RP&C considering the PECs and their impact. The following provides an explicit answer to each RQ and a brief outline of the theoretical contributions extracted from the findings. Answering RQ1 is based on the answering of the two sub-questions RQ1a and 1b.

> **RQ1**: How do planning environment characteristics impact information sharing during replenishment planning and control in fresh food retailing?

Very few papers have investigated PECs influence on information sharing, and no found study covers how the PECs affect the facets of information sharing considering the individual FFPs. Although acknowledging the PECs' impact on e.g. tactical planning level, current literature predominantly considers certain demand-related PECs to have an impact on information during RP&C. Thus, current approaches to RP&C differentiate according to demand type or processor level. This PhD study found that the PECs entail certain requirements to information sharing which are different from one PEC to another, entailing that information sharing should be differentiated at a product level. The PECs impact the information sharing in terms of six facets: content, timing, frequency, direction, modality and dynamism. As an example, while some PECs entail a higher or lower frequency in information sharing, other PECs entail more a need for ensuring appropriate timing. Yet other PECs entail that the information sharing (facets) may change during the year depending on e.g. raw material availability and thus have either a variable or fixed impact. Thus, considering the impact from PECs in terms of the facets entails effective information sharing which in turn allows more precise decision-making thereby improving the alignment of demand and supply. Further, considering the PECs from a processor point of view in terms of material requirement planning (MRP) and master production schedule (MPS) provides deeper understanding of whether the PEC impacts the raw material sourcing from suppliers successive (MRP) or the actual processing of raw material into ready products (MPS).

> **RQ1a:** What are the planning environment characteristics in fresh food retailing, and how are they characterised?

During different case studies 29 product, production, demand and supply PECs were identified as relevant to RP&C, with an explicit relation to either MRP, MPS or both at FFP processors as well as nine PECs for wholesaler and retail stores. Based on different mappings, it was identified how the individual PECs are characterised, specifically in terms of their description and area of impact. As opposed to current literature's focus on PECs only impacting on oneself, this PhD study predominantly explored the PECs from a FFP processor contingency point of view. It was found that the number of relevant PECs changes across animal type, entailing that while some FFPs are impacted by multiple PECs, other FFPs may only be impacted to a smaller extent. This added to the current understanding in literature that any PEC per se impacts any product. Further, the study led to the identification of 12 new planning environment characteristics: ageing, dairy prices, import non-EU to EU, product upgradeability, stability in meat classification, time of year for meat type, time of year for meat conformity, weather dependent supply, organic, slaughtering hierarchy and time of year for holidays. The identification and uncovering of the PECs and their characterisation has provided a more detailed understanding about specifically which PECs may be relevant for a certain type of product, as well as where, how and in what way does it relate to RP&C i.e. its characterisation.

> **RQ1b:** How is information sharing during replenishment planning and control in fresh food retailing characterised?

Based on a taxonomy with six facets of information sharing from the literature (content, frequency, timing, direction, modality and dynamism) and different case studies, this PhD study characterised information sharing in fresh food retailing. In particular, three areas seemed pertinent to this, namely demand type regarding whether information sharing is for normal or campaign demand, the creation and storing of the shared demand information as well as the age and time-coverage of the information. On the one hand, the findings confirmed current understanding about e.g. the discrepancy in information sharing during RP&C for normal vs campaign demand (i.e. different timing). On the other hand, the findings provided more detailed insight about the creation, storage, age and time-coverage of information sharing RP&C, with an additional reflection upon real-time information sharing.

> **RQ2**: How can wholesaler effectively plan and control replenishments according to the fresh food planning environment characteristics, and what is the impact on performance?

Three areas were found essential for RP&C, namely information sharing, forecasting evaluation and inventory control. Subsequent, considering the PECs in each of these areas is necessary to ensure effective decision-making which balances high product availability and freshness with low inventory and waste.

For information sharing, this study has developed 19 propositions for effective information sharing considering PECs as contingent on FFP processors' raw material availability (MRP) and processing into ready FFPs (MPS). The propositions relate to sourcing of raw material (4), processing flexibility (1), weather (3), shelf life and undesired ageing (5), enforced scarcity/excess (4) and special PECs (2). The propositions entail different information sharing and some propositions entail up to real-time frequency. However, no current studies were found to have investigated the effect of real-time POS-based information sharing on a same dataset for normal and campaign demand, and further comparison against product grouping according to processing method. This study investigated the effect of real-time point-of-sales (POS)-based information sharing during demand forecasting and inventory control across 50 FFPs. It further compared the real-time sharing to order-based information sharing and all scenarios were investigated for the effect when classifying products according to processing methods. Findings show that real-time POS-based information sharing generally outperforms order-based information sharing and that mixed information sharing at product level leads to the most significant improvement in performance. Further, the performance differs across demand type and processing method, and an increase in performance is generally accompanied by a marginal reduction in fill-rate, with a significant reduction in waste-levels and increase in freshness. The findings added to the current understanding of real-time information sharing, by providing insight into the need for both applying real-time and order-based information sharing during RP&C to ensure high availability with low waste.

For forecasting evaluation, this study developed a new differentiated forecasting accuracy measure, the wSLE, that considers product shelf life and its relation to following days demand. While current accuracy measures generally consider over-forecasting equally challenging as under-forecasting – or in case of quantile loss, consider under-forecasting more problematic, the wSLE differentiates the penalization of forecasting inaccuracy according to the relative importance of waste and fill-rate. An empirical evaluation of asymmetrical demand forecast evaluation across 17 FFPs considering fill-rate and waste was undertaken, with a comparison to three commonly used accuracy measures in retailing, namely RMSE, wMAPE and wQL. The results showed that the wSLE ensures higher levels of freshness and lower levels of waste compared to other accuracy measures. Further, the findings show that including the shelf life and the asymmetrical impact of over-forecasting with/without price reduction yields marginally lower service levels but an improved freshness of fresh food products and a lower inventory level. More specifically, the results showed that although the wSLE entails 0.6% lower fill-rate than wQL, the wSLE entail 52.6% less waste.

For inventory control, this study provided a four-dimensional RP&C model with guidelines for reflecting product perishability, coefficient of variation in demand, supply lead-time and (customer) order frequency during order decision-making. Further, this study extended the age-based replenishment policies of EWA and EWA_{SS} into a multi-product inventory heuristic, the EWA_{3SL}, that considers supplier fill-rate, price reduction, demand substitution and inventory substitution.

This study also provided insight about certain managerial implications related to implementation and application. As an example for wSLE, determining the different penalization values (under-/over-forecasting) for full assortments – and for EWA_{3SL}, determining the substitution factors when considering both demand and inventory. Apart from the implications in determining penalization/ substitution values at a product level for up to hundreds of FFPs, then depending on e.g. sociological and geographical differences, the values may also differ from one another to such extent that it entails a subsequent need for grouping the FFPs accordingly in order to circumvent the implications. In addition, this PhD study has focused on information sharing from a MRP and MPS requirements perspective, considering three (four) supply chain tiers. This has allowed a comprehensive product-level understanding of information sharing, while ensuring a supply chain wide holistic understanding as to the different facets of information sharing.

6.2. LIMITATIONS AND FUTURE WORK

This PhD study is not without certain limitations. The following highlight those of major concern with subsequent proposals for future research to reduce the limitations as well as allow further building of knowledge upon this work.

One limitation of this study relates to generalising the findings. Although the use of multiple case-studies certainly increases the generalisability in terms of deriving knowledge from several cases, they reflect an isolated understanding pertinent to the individual cases investigated. In this manner, the cases represented one chicken, one fish and one pork processor as well as one wholesaler, and hence a reflection of the contextual premises which cannot be uncovered following the paradigm of this study (i.e. critical realism), although acknowledging them to have an impact on the observed situation. Moreover, it should be noted that case studies imply "shedding light about some theoretical concepts or principles" (Yin, 2014, p. 40). Thus, future research should widen the case field to include more processors and uncover unique features, which in turn may alter the results of this analyses. Further, the focus on a wholesaler with decentralised decision-making also limits the application to organisational structures entailing centralised decision-making, which is predominant within grocery retailing. Thus, it would be of interest to investigate which adjustments are required to the findings of this study to fit such different contexts. Parallel to this, the selection of fresh food products (from the four animal types) limits the ability of generalising to fresh food assortments in general. Hence, future research should investigate the extent to which the findings in this PhD study apply, whether to other meat-types or other fresh food product types (e.g. ready-to-eat meals).

Another limitation of this study relates to the paradigmatic stance adopted in this PhD study, i.e. critical realism, and particularly the methodological approach. Although essentially a delimitation, the chosen research design limited the use of mere statistical inference from e.g. surveys, questionnaires, and simulations as well as distribution-based demand in e.g. inventory control models. Future research may benefit from taking a positivistic approach to allow detailed testing of variables in e.g. simulation, in turn creating both a deeper understanding of how the effects present in multiple different conditions as well as the intra-relationship between the variables. This is the case despite the inability for e.g. simulation to encompass multiple uncertainties and model the situation in its entirety (due to model complexity), and consequent the reflection of a virtual setup.

Finally, a limitation of this study relates to the propositions as well as proposed EWA_{3SL} and RP&C guidelines. Currently, the two are at conceptual stage without further testing. Empirical validation is needed to test both the applicability and impact in real-life settings with empirical data and information. Thus, future research should aim to compute the impact in terms of inventory control.

REFERENCES

Aastrup, J., Halldórsson, Á., 2008. Epistemological Role of Case Studies in Logistics: A Critical Realist Perspective. Int. J. Phys. Distrib. Logist. Manag. 38, 746–763.

Aastrup, J., Kotzab, H., 2009. Analyzing Out-Of-Stock in Independent Grocery Stores: An Empirical Study. Int. J. Retail Distrib. Manag. 37, 765–789.

Aastrup, J., Kotzab, H., 2010. Forty Years of Out-of-Stock Research - and Shelves are Still Empty. Int. Rev. Retail. Distrib. Consum. Res. 20, 147–164.

Adamides, E.D., Papachristos, G., Pomonis, N., 2012. Critical Realism in Supply Chain Research: Understanding the Dynamics of A Seasonal Goods Supply Chain. Int. J. Phys. Distrib. Logist. Manag. 42, 906–930.

Adams, F.G., Richey, R.G., Autry, C.W., Morgan, T.R., Gabler, C.B., 2014. Supply Chain Collaboration, Integration, and Relational Technology: How Complex Operant Resources Increase Performance Outcomes. J. Bus. Logist. 35, 299–317.

Adebanjo, D., 2009. Understanding Demand Management Challenges in Intermediary Food Trading: A Case Study. Supply Chain Manag. An Int. J. 14, 224–233.

Aggarwal, S., Srivastava, M.K., 2016. Towards a Grounded View of Collaboration in Indian Agri-Food Supply Chains: A Qualitative Investigation. Br. Food J. 118, 1085–1106.

Alftan, A., Kaipia, R., Loikkanen, L., Sepns, K., 2015. Centralised Grocery Supply Chain Planning: Improved Exception Management. Int. J. Phys. Distrib. Logist. Manag. 45, 237–259.

Alvarado-Valencia, J., Barrero, L.H., Önkal, D., Dennerlein, J.T., 2017. Expertise, Credibility of System Forecasts and Integration Methods in Judgmental Demand Forecasting. Int. J. Forecast. 33, 298–313.

Arbnor, I., Bjerke, B., 1997. Methodology for Creating Business Knowledge, 2nd ed. SAGE Publication, Inc., Lund, Sweden.

Assimakopoulos, V., Nikolopoulos, K., 2000. The Theta Model: A Decomposition Approach to Forecasting. Int. J. Forecast. 16, 521–530.

Attaran, M., Attaran, S., 2007. Collaborative Supply Chain Management: The most Promising Practice for Building Efficient and Sustainable Supply Chain. Bus. Process Manag. J. 13, 390–404.

Baihaqi, I., Sohal, A.S., 2013. The Impact of Information Sharing in Supply Chains on Organisational Performance: An Empirical Study. Prod. Plan. Control 24, 743–758.

Bakker, M., Riezebos, J., Teunter, R.H., 2012. Review of Inventory Systems with Deterioration Since 2001. Eur. J. Oper. Res. 221, 275–284.

Barratt, M., 2003. Positioning the Role of Collaborative Planning in Grocery Supply Chains. Int. J. Logist. Manag. 14, 53–66.

Barratt, M., Oke, A., 2007. Antecedents of Supply Chain Visibility in Retail Supply Chains: A Resource-Based Theory Perspective. J. Oper. Manag. 25, 1217–1233.

Barratt, M., Oliveira, A., 2001. Exploring the Experiences of Collaborative Planning Initiatives. Int. J. Phys. Distrib. Logist. Manag. 31, 266–289.

Beshel, B., 2010. An Introduction to Franchising. Washington.

Bhaskar, R., 1986. Scientific Realism and Human Emancipation. Verso, London, United Kingdom.

Blackburn, J., Scudder, G., 2009. Supply Chain Strategies for Perishable Products: The Case of Fresh Produce. Prod. Oper. Manag. 18, 129–137.

BlueYonder, 2017. Customer Experience in Grocery Retail: the Fresh Opportunity Customers in Fresh - A Global Survey of 4,000 Consumers Shine Light on Customer Experience in Fresh and Product Availability.

Bozarth, C.C., Warsing, D.P., Flynn, B.B., Flynn, E.J., 2009. The Impact of Supply Chain Complexity on Manufacturing Plant Performance. J. Oper. Manag. 27, 78–93.

Broekmeulen, R.A.C.M., van Donselaar, K.H., 2009. A Heuristic to Manage Perishable Inventory with Batch Ordering, Positive Lead-Times, and Time-Varying Demand. Comput. Oper. Res. 36, 3013–3018.

Broekmeulen, R.A.C.M., van Donselaar, K.H., 2017. Quantifying the Potential to Improve on Food Waste, Freshness and Sales for Perishables in Supermarkets. Int. J. Prod. Econ. 1–9.

Brooks, R., 2009. Overview: Scientific Paradigms. Horsens.

Brooks, R., 2013. Philosophy of Science & Methodology, 1st ed. Pearson Education Ltd., Harlow.

Brown, T.A., Bukovinsky, D.M., 2001. ECR and Grocery Retailing: An Exploratory Financial Statement Analysis. J. Bus. Logist. 22, 77–90.

Bryman, A., Bell, E., 2015. Business Research Methods, 4th ed. Oxford University Press, Oxford.

Buisman, M.E., Haijema, R., Bloemhof-Ruwaard, J.M., 2019. Discounting and Dynamic Shelf Life to Reduce Fresh Food Waste at Retailers. Int. J. Prod. Econ. 209, 274–284.

Byrne, P.J., Heavey, C., 2006. The Impact of Information Sharing and Forecasting in Capacitated Industrial Supply Chains: A Case Study. Int. J. Prod. Econ. 103, 420–437.

Cachon, G.P., Fisher, M., 2000. Supply Chain Inventory Management and the Value of Shared Information. Manage. Sci. 46, 1032–1048.

Caddy, I.N., Helou, M.M., 2007. Supply Chains and Their Management: Application of General Systems Theory. J. Retail. Consum. Serv. 14, 319–327.

Cai, S., Jun, M., Yang, Z., 2010. Implementing Supply Chain Information Integration in China: The Role of Institutional Forces and Trust. J. Oper. Manag. 28, 257–268.

Cao, M., Zhang, Q., 2011. Supply Chain Collaboration: Impact on Collaborative Advantage and Firm Performance. J. Oper. Manag. 29, 163–180.

Carr, A.S., Kaynak, H., 2007. Communication Methods, Information Sharing, Supplier Development and Performance: An Empirical Study of Their Relationships. Int. J. Oper. Prod. Manag. 27, 346–370.

Cengel, Y.A., Ghajar, A.J., 2015. Refrigeration and Freezing of Foods. In: Heat and Mass Transfer: Fundamentals and Applications. McGraw-Hill.

Chaudhary, V., Kulshrestha, R., Routroy, S., 2018. State-Of-the-Art Literature Review on Inventory Models for Perishable Products. J. Adv. Manag. Res. 15, 306–346.

Chen, F., Drezner, Z., Ryan, J.K., Simchi-levi, D., Chen, F., Drezner, Z., Ryan, J.K., 2000. Quantifying the Bullwhip Effect in a Simple Supply Chain: the Impact of Forecasting, Lead Times, and Information. Manage. Sci. 46, 436–443.

Chen, L., Mersereau, A.J., 2015. Analytics for Operational Visibility in the Retail Store: The Cases of Censored Demand and Inventory Record Inaccuracy. In: Agrawal, N., Smith, S. (Eds.), Retail Supply Chain Management, Quantitative Models and Empirical Studies. Springer-Verlag, New York, pp. 79–112.

Chen, J. V., Wang, C.L., Yen, D.C., 2014. A Causal Model for Supply Chain Partners Commitment. Prod. Plan. Control 25, 800–813.

Chen, X., Wu, S., Wang, X., Li, D., 2019. Optimal Pricing Strategy for The Perishable Food Supply Chain. Int. J. Prod. Res. 57, 2755–2768.

Choi, T.M., Li, J., Wei, Y., 2013. Will a supplier benefit from sharing good information with a retailer? Decis. Support Syst. 56, 131–139.

Choi, T.M., Sethi, S., 2010. Innovative Quick Response Programs: a Review. Int. J. Prod. Econ. 127, 1–12.

Chopra, S., Meindl, P., 2010. Supply Chain Management: Strategy, Planning and Operation. Pearson, New Jersey.

Christensen, Flemming M. M., Bojer, C.S., Dukovska-Popovska, I., Steger-Jensen, K., 2020a. Measuring Forecasting Accuracy Considering Product's Shelf Life: Effect on Availability and Waste. J. Clean. Prod. (under Rev.

Christensen, F.M.M., Dukovska-Popovska, I., Bojer, C.S., Steger-Jensen, K., 2019a. Asymmetrical Evaluation of Forecasting Models through Fresh Food Product Characteristics. In: Ameri, F., Stecke, K.E., Cieminski, G. von, Kiritsis, D. (Eds.), Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part II. Springer, pp. 155–163.

Christensen, F.M.M., Dukovska-Popovska, I., Steger-Jensen, K., 2017a. Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime. In: Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing - Proceedings, Part II. pp. 139–147.

Christensen, F.M.M., Dukovska-Popovska, I., Steger-Jensen, K., 2017b. Replenishment Planning of Fresh Meat Products: Case Study from a Danish Wholesaler. In: Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing - Proceedings, Part II. pp. 130–138.

Christensen, Flemming M. M., Jonsson, P., Dukovska-Popovska, I., Steger-Jensen, K., 2020b. Information Sharing for Replenishment Planning and Control in Fresh Food Supply Chains: A Planning Environment Perspective. Prod. Plan. Control (under Rev.

Christensen, F.M.M., Mantravadi, S., Dukovska-Popovska, I., Hvolby, H.-H., Steger-Jensen, K., Møller, C., 2019b. Horizontal Integration in Fresh Food Supply Chain. In: Ameri, F., Stecke, K.E., Cieminski, G. von, Kiritsis, D. (Eds.), Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part II. Springer, pp. 164–172.

Christensen, Flemming M M, Steger-jensen, K., Dukovska-popovska, I., 2020. Managing Perishable Multi-Product Inventory with Supplier Fill-Rate, Price Reduction and Substitution. In: Advances in Production Management Systems, Towards Smart and Digital Manufacturing - Proceedings Part II. pp. 640–649.

Christensen, F.M.M., Steger-Jensen, K., Dukovska-Popovska, I., 2017c. Product

Characteristics for Differentiated Replenishment Planning of Meat Products. In: International Symposium of Logistics, ISL. Ljubljana, pp. 594–601.

Corsten, D., Gruen, T.W., 2003. Desperataly Seeking Shelf Availability: An Examination of the Extent, the Causes, and the Efforts to Address Retail Out-Of-Stocks. Int. J. Retail Distrib. Manag. 31, 605–617.

Creswell, J.W., 2009. Research Design: Qualitative, Quantitative and Mixed Methods Approaches, 3rd ed. SAGE Publications Inc, Los Angeles.

Croson, R., Donohue, K., 2003. Impact of POS Data Sharing on Supply Chain Management: An Experimental Study. Prod. Oper. Manag. 12, 1–11.

Cui, R., Allon, G., Bassamboo, A., Van Mieghem, J.A., 2015. Information Sharing in Supply Chains: An Empirical and Theoretical Valuation. Manage. Sci. 61, 2803–2824.

Danese, P., 2007. Designing CPFR Collaborations: Insights from Seven Case Studies. Int. J. Oper. Prod. Manag. 27, 181–204.

de Moraes, C.C., de Oliveira Costa, F.H., Roberta Pereira, C., da Silva, A.L., Delai, I., 2020. Retail Food Waste: Mapping Causes and Reduction Practices. J. Clean. Prod. 256, 1–16.

De Toni, A.F., Zamolo, E., 2005. From a Traditional Replenishment System to Vendor-Managed Inventory: A Case Study From the Household Electrical Appliances Sector. Int. J. Prod. Econ. 96, 63–79.

Derrouiche, R., Neubert, G., Bouras, A., 2008. Supply Chain Management: a Framework to Characterize the Collaborative Strategies. Int. J. Comput. Integr. Manuf. 21, 426–439.

Dimitriadis, N.I., Koh, S.C.L., 2005. Information Flow and Supply Chain Management in Local Production Networks: The role of people and information systems. Prod. Plan. Control 16, 545–554.

Ding, M.J., Jie, F., Parton, K.A., Matanda, M.J., 2014. Relationships between quality of information sharing and supply chain food quality in the Australian beef processing industry. Int. J. Logist. Manag. 25, 85–108.

Disney, S.M., Towill, D.R., 2003a. The Effect of Vendor Managed Inventory (VMI) Dynamics on the Bullwhip Effect in Supply Chains. Int. J. Prod. Econ. 85, 199–215.

Disney, S.M., Towill, D.R., 2003b. Vendor-managed inventory and bullwhip reduction in a two-level supply chain. Int. J. Oper. Prod. Manag. 23, 625–651.

Distribution, T.I. of G., 2016. Ocado Group Annual Report 2016. Ocado.

Dong, Y., Shankar, V., Dresner, M.E., 2007. Efficient Replenishment in the

Distribution Channel. J. Retail. 83, 253–278.

Dreyer, H.C., Kiil, K., Dukovska-Popovska, I., Kaipia, R., 2018. Proposals for Enhancing Tactical Planning in Grocery Retailing with S&OP. Int. J. Phys. Distrib. Logist. Manag. 48, 114–138.

Duan, Q., Liao, T.W., 2013. A New Age-Based Replenishment Policy for Supply Chain Inventory Optimization of Highly Perishable Products. Int. J. Prod. Econ. 145, 658–671.

ECR Europe, 2003. Optimal Shelf Availability: Increasing Shopper Satisfaction at the Moment of Truth 64.

Edmunds, A., Morris, A., 2000. The Problem of Information Overload in Business Organizations: A Review of The Literature. Int. J. Inf. Manage. 20, 17–28.

Ehrenthal, J.C.F., Honhon, D., Van Woensel, T., 2014. Demand Seasonality in Retail Inventory Management. Eur. J. Oper. Res. 238, 527–539.

Eisenhardt, K.M., 1989. Building Theories from Case Study Research. Acad. Manag. Rev. 14, 532–550.

Endsley, M.R., 2000. Theoretical Underpinnings of Situation Awareness: A Critical Review. In: Endsley, M.R., Garland, D.J. (Eds.), Situation Awareness Analysis and Measurement. Lawrence ErlbaumAssociates Inc., New Jersey, pp. 3–32.

Entrup, M.L., 2005. Advanced Planning in Fresh Food Industries, Integrating Shelf Life into Production Planning. Physica-Verlag Heidelberg, Berlin.

Eriksson, M., Strid, I., Hansson, P.-A., 2014. Waste of Organic and Conventional Meat and Dairy Products — A Case Study from Swedish Retail. Resour. Conserv. Recycl. 83, 44–52.

Ettouzani, Y., Yates, N., Mena, C., 2012. Examining Retail On Shelf Availability: Promotional Impact and a Call for Research. Int. J. Phys. Distrib. Logist. Manag. 42, 213–243.

Evans, J., 2016. Effects of Food and Beverage Storage, Distribution, Display, and Consumer Handling on Shelf Life. In: Subramaniam, P. (Ed.), The Stability and Shelf Life of Food. Woodhead Publishing, Cambridge, pp. 107–140.

Fang Du, X., Leung, S.C.H., Long Zhang, J., Lai, K.K., 2009. Procurement of Agricultural Products using the CPFR Approach. Supply Chain Manag. An Int. J. 14, 253–258.

Fattibene, D., Bianchi, M., 2017. Fighting against Food Losses and Waste: An EU Agenda, Istituto Affari Internazionali (IAI).

Fawcett, S.E., Osterhaus, P., Magnan, G.M., Brau, J.C., McCarter, M.W., 2007. Information Sharing and Supply Chain Performance: The Role of Connectivity and Willingness. Supply Chain Manag. 12, 358–368.

Ferguson, M.E., Ketzenberg, M.E., 2006. Information Sharing to Improve Retail Product Freshness of Perishables. Prod. Oper. Manag. 15, 57–73.

Ferguson, M.E., Koenigsberg, O., 2007. How Should a Firm Manage Deteriorating Inventory? Prod. Oper. Manag. 16, 306–321.

Fisher, M.L., Raman, A., 2010. Flexible Supply Chains. In: The New Science of Retailing. Harvard Business Press, Boston, pp. 105–131.

Fleischmann, B., Meyr, H., Wagner, M., 2015. Advanced Planning & Structure of Advanced Planning Systems: In: Stadtler, H., Kilger, C., Meyr, H. (Eds.), Supply Chain Management and Advanced Planning. Springer Berlin Heidelberg, New York, pp. 81–106.

Flynn, B.B., Sakakibara, S., Schroeder, R.G., Bates, K.A., Flynn, E.J., 1990. Empirical Research Methods in Operations Management. J. Oper. Manag. 9, 250–284.

Fransoo, J.C., Wouters, M.J.F., 2000. Measuring the Bullwhip Effect in the Supply Chain. Supply Chain Manag. 5, 78–89.

Fredriksson, A., Liljestrand, K., 2015. Capturing Food Logistics: A Literature Review and Research Agenda. Int. J. Logist. Res. Appl. 18, 16–34.

Gneiting, T., 2011a. Quantiles as Optimal Point Forecasts. Int. J. Forecast. 27, 197–207.

Gneiting, T., 2011b. Making and Evaluating Point Forecasts. J. Am. Stat. Assoc. 106, 746–762.

Goyal, S.K., Giri, B.C., 2001. Recent Trends in Modeling of Deteriorating Inventory. Eur. J. Oper. Res. 134, 1–16.

Granger, C.W.J., 1999. Outline of Forecast Theory Using Generalized Cost Functions. Spanish Econ. Rev. 1, 161–173.

Granger, C.W.J., Pesaran, M.H., 2000. Economic and Statistical Measures of Forecast Accuracy. J. Forecast. 19, 537–560.

Gruen, T.W., Corsten, D.S., Bharadwaj, S., 2002. Retail Out-of-Stocks: A Worldwide Examination of Extent, Causes and Consumer Responses. Grocery Manufacturers of America, Washington.

Guba, E.G., Lincoln, Y.S., 1994. Competing Paradigms in Qualitative Research. In: Handbook of Qualitative Research. SAGE Publication, Inc., Thousand Oakes, pp. 105–117.

Gustavsson, M., Jonsson, P., 2008. Perceived Quality Deficiencies of Demand Information and Their Consequences. Int. J. Logist. Res. Appl. 11, 295–312.

Ha, B.-C., Park, Y.-K., Cho, S., 2011. Suppliers' Affective Trust and Trust in Competency in Buyers, its Effect on Collaboration and Logistics Efficiency. Int. J. Oper. Prod. Manag. 31, 56–77.

Hanke, J.E., Wichern, D.W., 2009. Business Forecasting, 9th ed. Pearson Prentice Hall, New Jersey.

Hartzel, K.S., Wood, C.A., 2017. Factors that Affect the Improvement of Demand Forecast Accuracy through Point-of-Sale Reporting. Eur. J. Oper. Res. 260, 171–182.

Hayes, R.H., Wheelwright, S.C., 1979. Link Manufacturing Process and Product Life Cycles. Harv. Bus. Rev. 57, 133–140.

He, Y., Li, D., Wu, S.J., Shi, C., 2018. Quality and Operations Management in Food Supply Chain. J. Food Qual. 2018, 1–14.

Heese, H.S., Kemahlioglu-Ziya, E., 2016. Don't Ask, Don't Tell: Sharing Revenues With a Dishonest Retailer. Eur. J. Oper. Res. 248, 580–592.

Hollmann, R.L., Scavarda, L.F., Thomé, A.M.T., 2015. Collaborative Planning, Forecasting and Replenishment: A Literature Review. Int. J. Product. Perform. Manag. 64, 971–993.

Holweg, C., Teller, C., Kotzab, H., 2016. Unsaleable Grocery Products, Their Residual Value and Instore Logistics. Int. J. Phys. Distrib. Logist. Manag. 46, 634–658.

Huang, G.Q., Lau, J.S.K., Mak, K.L., 2003. The Impacts of Sharing Production Information on Supply Chain Dynamics: A Review of the Literature. Int. J. Prod. Res. 41, 1483–1517.

Huang, S., Guan, X., Chen, Y.J., 2018. Retailer Information Sharing with Supplier Encroachment. Prod. Oper. Manag. 27, 1133–1147.

Huber, J., Gossmann, A., Stuckenschmidt, H., 2017. Cluster-Based Hierarchical Demand Forecasting for Perishable Goods. Expert Syst. Appl. 76, 140–151.

Hübner, A.H., 2011. Retail Category Management Decision Support Systems. In: Lecture Notes in Economics and Mathematical Systems. Springer.

Hübner, A.H., Kuhn, H., Sternbeck, M.G., 2013. Demand and Supply Chain Planning in Grocery Retail: an Operations Planning Framework. Int. J. Retail Distrib. Manag. 41, 512–530.

Hung, W.H., Ho, C.F., Jou, J.J., Tai, Y.M., 2011. Sharing Information Strategically in a Supply Chain: Antecedents, Content and Impact. Int. J. Logist. Res. Appl. 14, 111–133.

Hvolby, H., Steger-Jensen, K., 2015. Managing Cannibalization of Perishable Food Products in the Retail Sector. Procedia Comput. Sci. 64, 1051–1056.

Hyndman, R.J., 2006. Another Look at Forecast-Accuracy Metrics for Intermittent Demand. Foresight Int. J. Appl. Forecast. 43–46.

Hyndman, R.J., Khandakar, Y., 2008. Automatic Time Series Forecasting: the forecast Package for R. J. Stat. Softw. 27, 1–23.

Hyndman, R.J., Koehler, A.B., 2006. Another Look at Measures of Forecast Accuracy. Int. J. Forecast. 22, 679–688.

Hyndman, R.J., Koehler, A.B., Ord, J.K., Snyder, R.D., 2008. Forecasting with Exponential Smoothing, The State Space Aproach, Springer Series in Statistics. Springer Berlin Heidelberg, Berlin.

Ivert, L.K., Dukovska-Popovska, I., Kaipia, R., Fredriksson, A., Dreyer, H.C., Johansson, M.I., Chabada, L., Damgaard, C.M., Tuomikangas, N., 2015. Sales and Operations Planning: Responding to the Needs of Industrial Food Producers. Prod. Plan. Control 26, 280–295.

J.S., N., Chilkapure, A., Pillai, V.M., 2019. Literature Review on Supply Chain Collaboration: Comparison of Various Collaborative Techniques. J. Adv. Manag. Res. 16, 537–562.

Jacobsen, P.Ø., Bjerre, M., 2015. Effekt & Effektivitet, Dansk Dagligvarehandel 2003-2013. Copenhagen Business School.

Jin, Y., Williams, B.D., Tokar, T., Waller, M.A., 2015. Forecasting With Temporally Aggregated Demand Signals in A Retail Supply Chain. J. Bus. Logist. 36, 199–211.

Jonsson, P., Holmström, J., 2016. Future of Supply Chain Planning: Closing the Gaps Between Practice and Promise. Int. J. Phys. Distrib. Logist. Manag. 46, 62–81.

Jonsson, P., Mattsson, S.-A., 2003. The Implications of Fit between Planning Environments and Manufacturing Planning and Control Methods. Int. J. Oper. Prod. Manag. 23, 872–900.

Jonsson, P., Mattsson, S.-A., 2013. The Value of Sharing Planning Information in Supply Chains. Int. J. Phys. Distrib. Logist. Manag. 43, 282–299.

Jonsson, P., Myrelid, P., 2016. Supply Chain Information Utilisation: Conceptualisation and Antecedents. Int. J. Oper. Prod. Manag. 36, 1769–1799.

Kache, F., Seuring, S., 2014. Linking Collaboration and Integration to Risk and Performance in Supply Chains via a Review of Literature Reviews. Supply Chain Manag. An Int. J. 19, 664–682.

Kähkönen, A.-K., Tenkanen, M., 2010. The impact of power on information sharing in the Finnish food industry. Br. Food J. 112, 821–835.

Kaipia, R., Dukovska-Popovska, I., Loikkanen, L., 2013. Creating Sustainable Fresh Food Supply Chains through Waste Reduction. Int. J. Phys. Distrib. Logist. Manag. 43, 262–276.

Kaipia, R., Hartiala, H., 2006. Information-Sharing in Supply Chains: Five Proposals on How to Proceed. Int. J. Logist. Manag. 17, 377–393.

Kaipia, R., Holmström, J., 2007. Selecting the Right Planning Approach for a Product. Supply Chain Manag. An Int. J. 12, 3–13.

Kaipia, R., Holmström, J., Småros, J., Rajala, R., 2017. Information Sharing for Sales and Operations Planning: Contextualized Solutions and Mechanisms. J. Oper. Manag. 52, 15–29.

Kaipia, R., Korhonen, H., Hartiala, H., 2006. Planning Nervousness in a Demand Supply Network: An Empirical Study. Int. J. Logist. Manag. 17, 95–113.

Kamalapur, R., Lyth, D., Houshyar, A., 2013. Benefits of CPFR and VMI Collaboration Strategies: a Simulation Study. J. Oper. Supply Chain Manag. 6, 59–73.

Kehoe, D.F., Boughton, N.J., 2001. New Paradigms in Planning and Control across Manufacturing Supply Chains - The Utilisation of Internet Technologies. Int. J. Oper. Prod. Manag. 21, 582–593.

Keller, L.R., 1989. The Role Of Generalized Utility Theories In Decision Analysis. Inf. Decis. Technol. 15, 259–271.

Kembro, J., Näslund, D., 2014. Information Sharing in Supply Chains, Myth or Reality? A Critical Analysis of Empirical Literature. Int. J. Phys. Distrib. Logist. Manag. 44, 179–200.

Kembro, J., Selviaridis, K., 2015. Exploring Information Sharing in the Extended Supply Chain: An Interdependence Perspective. Supply Chain Manag. 20, 455–470.

Kembro, J., Selviaridis, K., Näslund, D., 2014. Theoretical Perspectives on Information Sharing in Supply Chains: a Systematic Literature Review and Conceptual Framework. Supply Chain Manag. An Int. J. 19, 609–625.

Kiil, K., Dreyer, H.C., Hvolby, H.H., Chabada, L., 2018a. Sustainable Food Supply Chains: The Impact of Automatic Replenishment in Grocery Stores. Prod. Plan. Control 29, 106–116.

Kiil, K., Hvolby, H.-H., Trienekens, J., Behdani, B., Strandhagen, J.O., 2019. From Information Sharing to Information Utilization in Food Supply Chains. Int. J. Inf. Syst. Supply Chain Manag. 12, 85–109.

Kiil, K., Hvolby, H.H., Fraser, K., Dreyer, H., Strandhagen, J.O., 2018b. Automatic Replenishment of Perishables in Grocery Retailing: The Value of Utilizing Remaining Shelf Life Information. Br. Food J. 120, 2033–2046.

Klein, R., Rai, A., 2009. Interfirm Strategic Information Flows in Logistics Supply Chain Relationships. MIS Q. 33, 735–762.

Kolassa, S., 2016. Evaluating Predictive Count Data Distributions in Retail Sales Forecasting. Int. J. Forecast. 32, 788–803.

Kolassa, S., 2020. Why The “Best” Point Forecast Depends on the Error or

Accuracy Measure. Int. J. Forecast. 36, 208–211.

Kolassa, S., Schütz, W., 2007. Advantages of the MAD/Mean Ratio over the MAPE. Foresight Int. J. Appl. Forecast. 40–43.

Kong, F., Singh, R.P., 2016. Chemical Deterioration and Physical Instability of Foods and Beverages. In: Subramaniam, P. (Ed.), The Stability and Shelf Life of Food. Woodhead Publishing, Cambridge, pp. 43–76.

Königer, P., Janowitz, K., 1995. Drowning in Information, But Thirsty for Knowledge. Int. J. Inf. Manage. 15, 5–16.

Kourentzes, N., Trapero, J.R., Barrow, D.K., 2020. Optimising Forecasting Models for Inventory Planning. Int. J. Prod. Econ. xx–xx.

Kuhn, H., Sternbeck, M.G., 2013. Integrative retail logistics: An exploratory study. Oper. Manag. Res. 6, 2–18.

Kulp, S.C., 2002. Effect of Information Precision Reliability Retailer and on Information Relationships. acounting Rev. 77, 653–677.

Kummu, M., de Moel, H., Porkka, M., Siebert, S., Varis, O., Ward, P.J., 2012. Lost Food, Wasted Resources: Global Food Supply Chain Losses and their Impacts on Freshwater, Cropland, and Fertiliser Use. Sci. Total Environ. 438, 477–489.

Kurt Salmon Associates, and J.I., 1998. ECR Industry Benchmarking Survey. Joint Industry Project on ECR.

Kurt Salmon Associates, I., 1993. Efficient Consumer Response - Enhancing Consumer Value in the Grocery Industry. Washington, DC.

Lambert, D.M., 2008. Supply Chain Management - Processes, Partnership, Performance. Supply Chain Management Institute, Sarasota.

Lee, C.H., Ha, B.C., 2018. The Impact of Buyer-Supplier Relationships' Social Capital on Bi-Directional Information Sharing in the Supply Chain. J. Bus. Ind. Mark. 33, 325–336.

Lee, C.K.H., Choy, K.L., Ho, G.T.S., Lin, C., 2016. A Cloud-Based Responsive Replenishment System in a Franchise Business Model using a Fuzzy Logic Approach. Expert Syst. 33, 14–29.

Lee, H.L., So, K.C., Tang, C.S., 2000. The Value of Information Sharing in a Two-Level Supply Chain. Manage. Sci. 46, 626–643.

Lee, T.-H., 2007. Loss Functions in Time Series Forecasting, White paper. Riverside.

Li, Y., Ye, F., Sheu, C., 2014. Social Capital, Information Sharing and Performance: Evidence from China. Int. J. Oper. Prod. Manag. 34, 1440–1462.

Lowalekar, H., Ravichandran, N., 2017. A Combined Age-and-Stock Based Policy for Ordering Blood Units in Hospital Blood Banks. Int. Trans. Oper. Res. 24, 1561–1586.

Lummus, R.R., Vokurka, R.J., 1999. Defining Supply Chain Management: a Historical Perspective and Practical Guidelines. Ind. Manag. Data Syst. 99, 11–17.

Lusiantoro, L., Yates, N., Mena, C., Varga, L., 2018. A Refined Framework of Information Sharing in Perishable Product Supply Chains, International Journal of Physical Distribution & Logistics Management.

Man, C.M.D., 2016. Food Storage Trials. In: Subramaniam, P. (Ed.), The Stability and Shelf Life of Food. Woodhead Publishing, Cambridge, pp. 171–198.

Mantravadi, S., Møller, C., Christensen, F.M.M., 2018. Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration. In: International Conference on Smart Systems and Technologies (SST): IEEE Region 8, Croatian Academy of Engineering. pp. 133–137.

Marquès, G., Thierry, C., Lamothe, J., Gourc, D., 2010. A Review of Vendor Managed Inventory (VMI): From Concept to Processes. Prod. Plan. Control 21, 547–561.

McKinnon, A.C., Mendes, D., Nababteh, M., 2007. In-Store Logistics: An Analysis of On-Shelf Availability and Stockout Responses for Three Product Groups. Int. J. Logist. Res. Appl. 10, 251–268.

Mehdiyev, N., Enke, D., Fettke, P., Loos, P., 2016. Evaluating Forecasting Methods by Considering Different Accuracy Measures. Procedia - Procedia Comput. Sci. 95, 264–271.

Mena, C., Adenso-Diaz, B., Yurt, O., 2011. The Causes of Food Waste in the Supplier-Retailer Interface: Evidences from the UK and Spain. Resour. Conserv. Recycl. 55, 648–658.

Mena, C., Humphries, A., Wilding, R., 2009. A comparison of inter- and intra-organizational relationships - Two case studies from UK food and drink industry. Int. J. Phys. Distrib. Logist. Manag. 39, 762–784.

Mena, C., Terry, L.A., Williams, A., Ellram, L.M., 2014. Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector. Int. J. Prod. Econ. 152, 144–158.

Mingers, J., 2004. Real-izing Information Systems: Critical Realism as An Underpinning Philosophy for Information Systems. Inf. Organ. 14, 87–103.

Mingers, J., 2011. The Contribution of Systemic Thought to Critical Realism. J. Crit. Realis. 10, 303–330.

Moberg, C.R., Cutler, B.D., Gross, A., Speh, T.W., 2002. Identifying Antecedents of Information Exchange within Supply Chains. Int. J. Phys. Distrib. Logist.

Manag. 32, 755–770.

Mohr, J., Nevin, J.R., 1990. Communication Strategies in Marketing Channels: A Theoretical Perspective. J. Mark. 54, 36–51.

Montoya-Torres, J.R., Ortiz-Vargas, D.A., 2014. Collaboration and Information Sharing in Dyadic Supply Chains: A Literature Review over the Period 2000–2012. Estud. Gerenciales 30, 343–354.

Moussaoui, I., Williams, B.D., Hofer, C., Aloysius, J.A., Waller, M.A., 2016. Drivers of Retail On-Shelf Availability: Systematic Review, Critical Assessment, and Reflections on the Road Ahead. Int. J. Phys. Distrib. Logist. Manag. 46, 516–535.

Myers, M.B., Daugherty, P.J., Autry, C.W., 2000. The Effectiveness of Automatic Inventory Replenishment in Supply Chain Operations: Antecedents and Outcomes. J. Retail. 76, 455–481.

Myrelid, P., Jonsson, P., 2019. Determinants of Information Quality in Dyadic Supply Chain Relationships. Int. J. Logist. Manag. 30, 356–380.

Nachtmann, H., Waller, M.A., Rieske, D.W., 2010. The Impact of Point-of-Sale Data Inaccuracy and Inventory Record Data Errors. J. Bus. Logist. 31, 149–158.

Nahmias, S., Pierskalla, W.P., 1973. Optimal Ordering Policies For a Product That Perishes in Two Periods Subject to Stochastic Demand. Nav. Res. Logist. Q. 20, 207–229.

Nakandala, D., Lau, H.C.W., 2019. Innovative Adoption of Hybrid Supply Chain Strategies in Urban Local Fresh Food Supply Chain. Supply Chain Manag. 24, 241–255.

Nakandala, D., Samaranayake, P., Lau, H., 2017. Modelling Information Flow and Sharing Matrix for Fresh Food Supply Chains. Bus. Process Manag. J. 23, 108–129.

Narayanan, A., Sahin, F., Robinson, E.P., 2019. Demand and Order-Fulfillment Planning: The Impact of Point-of-Sale Data, Retailer Orders and Distribution Center Orders on Forecast Accuracy. J. Oper. Manag. 65, 468–486.

Narayanan, V.G., Raman, A., 2004. Aligning Incentives in Supply Chains. Harv. Bus. Rev. 82, 94–102.

Nielsen, 2017. Western European FMCG Report Q4 2016.

Nielsen, 2018. Western European FMCG Report Q4 2017.

Okasha, S., 2002. Philosophy of Science, A Very Short Introduction. Oxford University Press, New York.

Olhager, J., Rudberg, M., 2002. Linking Manufacturing Strategy Decisions on Process Choice with Manufacturing Planning and Control Systems. Int. J.

Prod. Res. 40, 2335–2351.

Pålsson, H., Johansson, O., 2009. Supply Chain Integration Obtained through Uniquely Labelled Goods: A Survey of Swedish Manufacturing Industries. Int. J. Phys. Distrib. Logist. Manag. 39, 28–46.

Paltridge, B., Starfield, S., 2007. Thesis and Dissertation Writing in a Second Laguage. Routledge.

Panahifar, F., Heavey, C., Byrne, P., Fazlollahtabar, H., 2015. A Framework for Collaborative Planning, Forecasting and Replenishment (CPFR), Journal of Enterprise Information Management.

Parfitt, J., Barthel, M., MacNaughton, S., 2010. Food Waste within Food Supply Chains: Quantification and Potential for Change to 2050. Philos. Trans. R. Soc. B Biol. Sci. 365, 3065–3081.

Paulraj, A., Lado, A.A., Chen, I.J., 2008. Inter-Organizational Communication as a Relational Competency: Antecedents and Performance Outcomes in Collaborative Buyer-Supplier Relationships. J. Oper. Manag. 26, 45–64.

Petropoulos, F., Kourentzes, N., Nikolopoulos, K., Siemsen, E., 2018. Judgmental Selection of Forecasting Models. J. Oper. Manag. 60, 34–46.

Pramatari, K., Miliotis, P., 2008. The Impact of Collaborative Store Ordering on Shelf Availability. Supply Chain Manag. An Int. J. 13, 49–61.

Pramatari, K., Papakiriakopoulos, D., 2002. New Forms of CPFR. ECR J. 2, 38–43.

Priyadarshi, R., Panigrahi, A., Routroy, S., Garg, G.K., 2019. Demand Forecasting at Retail Stage for Selected Vegetables: A Performance Analysis. J. Model. Manag. 14, 1042–1063.

Raafat, F., 1991. Survey of Literature on Continuously Deteriorating Inventory Models. J. Oper. Res. Soc. 42, 27–37.

Raghunathan, S., Yeh, A.B., 2001. Beyond EDI: Impact of Continuous Replenishment Program (CRP) Between a Manufacturer and Its Retailers. Inf. Syst. Res. 12, 406–419.

Raman, A., DeHoratius, N., Ton, Z., 2001. Execution: The Missing Link in Retail Operations. Calif. Manage. Rev. 43, 136–152.

Ramos, P., Santos, N., Rebelo, R., 2015. Performance of State Space and ARIMA Models for Consumer Retail Sales Forecasting. Robot. Comput. Integr. Manuf. 34, 151–163.

RELEX, 2020. Planning for Every Future in Grocery Retail, Survey-Based Research Study.

Retail Institute Scandinavia, 2017. Dansk Dagligvarehandel, Prognose 2027. Kgs. Lyngby.

Reyes, P.M., Bhutta, K., 2005. Efficient Consumer Response: Literature Review. Int. J. Integr. Supply Manag. 1, 346–386.

Robertson, G.L., 2016. Packaging And Food and Beverage Shelf Life. In: Subramaniam, P. (Ed.), The Stability and Shelf Life of Food. Woodhead Publishing, Cambridge, pp. 77–106.

Romsdal, A., 2014. Differentiated Production Planning and Control in Food Supply Chains.

Romsdal, A., Strandhagen, J.O., Dreyer, H.C., 2014. Can Differentiated Production Planning and Control enable both Responsiveness and Efficiency in Food Production ? Int. J. Food Syst. Dyn. 34–43.

Sabath, R.E., Autry, C.W., Daugherty, P.J., 2001. Automatic Replenishment Programs: the Impact of Organizational Structure. J. Bus. Logist. 22, 91–105.

Sari, K., 2008. On the Benefits of CPFR and VMI: a Comparative Simulation Study. Int. J. Prod. Econ. 113, 575–586.

Schein, E.H., 1999. Process Consultation Revisited, Bulding the Helping Relationship. Addison-Wesley.

Shenton, A.K., 2004. Strategies for Ensuring Trustworthiness in Qualitative Research Projects. Educ. Inf. 63–75.

Sheu, C., Yen, H.R., Chae, B., 2006. Determinants of Supplier-Retailer Collaboration: Evidence from an International Study. Int. J. Oper. Prod. Manag. 26, 24–49.

Siddh, M.M., Soni, G., Jain, R., 2015. Perishable Food Supply Chain Quality (PFSCQ) - A Structured Review and Implications for Future Research. J. Adv. Manag. Res. 12, 292–313.

Silver, E.A., Pyke, D.F., Peterson, R., 1998. Inventory Management and Production Planning and Scheduling. John Wiley & Sons, Inc., Hoboken.

Simatupang, T.M., Sridharan, R., 2005a. The Collaboration Index: a Measure for Supply Chain Collaboration. Int. J. Phys. Distrib. Logist. Manag. 35, 44–62.

Simatupang, T.M., Sridharan, R., 2005b. An Integrative Framework for Supply Chain Collaboration. Int. J. Logist. Manag. 16, 257–274.

Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E., 2003. Designing & Managing the Supply Chain - Concepts, Strategies & Case Studies, 2nd ed. McGraw-Hill, New York.

Småros, J., 2007. Forecasting Collaboration in the European Grocery Sector: Observations from a Case Study. J. Oper. Manag. 25, 702–716.

Småros, J., Lehtonen, J., Appelqvist, P., Holmström, J., 2003. The Impact of Increasing Demand Visibility on Production and Inventory Control

Efficiency. J. Phys. Distrib. Logist. Manag. 33, 336–354.

Spenhoff, P., Semini, M., Alfnes, E., Strandhagen, J.O., 2014. The Fit of Planning Methods for the Part Manufacturing Industry, a Case Study. Adv. Manuf. 2, 165–172.

Spens, K.M., Kovács, G., 2006. A Content Analysis of Research Approaches in Logistics Research. Int. J. Phys. Distrib. Logist. Manag. 36, 374–390.

Ståhl Elvander, M., Sarpola, S., Mattsson, S., 2007. Framework for Characterizing the Design of VMI Systems. Int. J. Phys. Distrib. Logist. Manag. 37, 782–798.

Stank, T.P., Daugherty, P.J., Autry, C.W., 1999. Collaborative Planning: Supporting Automatic Replenishment Programs. Supply Chain Manag. An Int. J. 4, 75–85.

Stenmarck, Å., Hanssen, O.J., Silvennoinen, K., Katajajuuri, J.-M., Werge, M., 2011. Initiatives on Prevention of Food Waste in the Retail and Wholesale Trades. Stockholm.

Stenmarck, Å., Jensen, C., Quested, T., Moates, G., 2016. Estimates of European food waste levels. FUSIONS Reducing Food Waste through Social Innovation |.

Steven Nahmias, 1982. Perishable Inventory Theory : A Review. Oper. Res. 30, 680–708.

Tan, K.C., Kannan, V.R., Hsu, C., Leong, G.K., 2010. Supply Chain Information and Relational Alignments: Mediators of EDI on Firm Performance. Int. J. Phys. Distrib. Logist. Manag. 40, 377–394.

Taylor, D.H., Fearne, A., 2009. Demand management in fresh food value chains: A framework for analysis and improvement. Supply Chain Manag. 14, 379–392.

Teller, C., Holweg, C., Reiner, G., Kotzab, H., 2018. Retail Store Operations and Food Waste. J. Clean. Prod. 185, 981–997.

Thatte, A.A., Rao, S.S., Ragu-Nathan, T.S., 2012. Impact of SCM Practices of a Firm on Supply Chain Responsiveness and Competitive Advantage of a Firm. J. Appl. Bus. Res. 29, 499–530.

The Institute of Grocery Distribution, 2019. Retail in 2025.

Thomé, A.M.T., Hollmann, R.L., do Carmo, L.F.R.R.S., 2014. Research Synthesis in Collaborative Planning Forecast and Replenishment. Ind. Manag. Data Syst. 114, 949–965.

Trapero, J.R., Cardós, M., Kourentzes, N., 2019. Quantile Forecast Optimal Combination to Enhance Safety Stock Estimation. Int. J. Forecast. 35, 239–250.

Tyan, J., Wee, H.M., 2003. Vendor Managed Inventory: A Survey of the Taiwanese

Grocery Industry. J. Purch. Supply Manag. 9, 11–18.

van Donselaar, K., van Woensel, T., Broekmeulen, R., Fransoo, J., 2006. Inventory control of perishables in supermarkets. Int. J. Prod. Econ. 104, 462–472.

van Donselaar, K.H., Gaur, V., Woensel, T. Van, Rob, A.C.M., Fransoo, J.C., Donselaar, K.H. Van, Woensel, T. Van, Broekmeulen, R.A.C.M., Fransoo, T.C., 2010. Ordering Behavior in Retail Stores and Implications for Automated Replenishment. Manage. Sci. 56, 766–784.

Van Donselaar, K.H., Peters, J., De Jong, A., Broekmeulen, R.A.C.M., 2016. Analysis and Forecasting of Demand during Promotions for Perishable Items. Int. J. Prod. Econ. 172, 65–75.

van Hoek, R., Harrison, A., 2008. Logistics Management and Strategy, Competing through the Supply Chain, 3rd ed. Prentice Hall, Harlow.

van Kampen, T.J., Akkerman, R., van Donk, D.P., 2012. SKU Classification: a Literature Review and Conceptual Framework. Int. J. Oper. Prod. Manag. 32, 850–876.

Vanpoucke, E., Boyer, K.K., Vereecke, A., 2009. Supply Chain Information Flow Strategies: an Empirical Taxonomy. Int. J. Oper. Prod. Manag. 29, 1213–1241.

Verheijen, B., 2010. Drivers for Supply Chain Collaboration in Practice. In: PhD-Thesis: Vendor-Buyer Coordination in Supply Chains. Erasmus Research Institute of Management, Rotterdam, pp. 9–42.

VICS, 2004. Collaborative Planning, Forecasting, and Replenishment., Collaborative Planning, Forecasting and Replenishment (CPFR®), An Overview.

VICS, 2010. Linking CPFR and S&OP : A Roadmap to Integrated Business Planning.

Vigtil, A., 2007. Information Exchange in Vendor Managed Inventory. Int. J. Phys. Distrib. Logist. Manag. 37, 131–147.

Voss, C., Tsikriktsis, N., Frohlich, M., 2002. Case Research in Operations Management. Int. J. Oper. Prod. Manag. 22, 195–219.

Wänström, C., Jonsson, P., 2006. The impact of Outsourcing on Materials Planning. J. Manuf. Technol. Manag. 17, 561–584.

Watabaji, M.D., Molnar, A., Weaver, R.D., Dora, M.K., Gellynck, X., 2016. Information Sharing and its Integrative Role: An Empirical Study of the Malt Barley Value Chain in Ethiopia. Br. Food J. 118, 3012–3029.

Whipple, J.M., Russell, D., 2007. Building Supply Chain Collaboration: a Typology of Collaborative Approaches. Int. J. Logist. Manag. 18, 174–196.

Williams, B.D., Waller, M.A., 2010. Creating Order Forecasts: Point-of-Sale or

Order History? J. Bus. Logist. 31, 231–251.

Williams, B.D., Waller, M.A., 2011. Top-Down Versus Bottom-Up Demand Forecasts: The Value of Shared Point-of-Sale Data in the Retail Supply Chain. J. Bus. Logist. 32, 17–26.

Williams, B.D., Waller, M.A., Ahire, S., Ferrier, G.D., 2014. Predicting Retailer Orders with POS and Order Data: the Inventory Balance Effect. Eur. J. Oper. Res. 232, 593–600.

Xu, K., Dong, Y., Xia, Y., 2015. "Too little" or "Too late": The Timing of Supply Chain Demand Collaboration. Eur. J. Oper. Res. 241, 370–380.

Yigitbasioglu, O.M., 2010. Information Sharing with Key Suppliers: a Transaction Cost Theory Perspective. Int. J. Phys. Distrib. Logist. Manag. 40, 550–578.

Yin, R.K., 2014. Case Study Research: Design and Methods, 5th ed. SAGE Publications Inc, California.

Yu, W., Jacobs, M.A., Salisbury, W.D., Enns, H., 2013. The Effects of Supply Chain Integration on Customer Satisfaction and Financial Performance: An Organizational Learning Perspective. Int. J. Prod. Econ. 146, 346–358.

Zammori, F., Braglia, M., Frosolini, M., 2009. A Standard Agreement for Vendor Managed Inventory. Strateg. Outsourcing An Int. J. 2, 165–186.

Zhou, H., Benton, W.C., 2007. Supply Chain Practice and Information Sharing. J. Oper. Manag. 25, 1348–1365.

APPENDICES

Theoretical Background:

Appendix A: Planning Environment Characteristics - Literature

Appendix B: Empirical Studies on Point-of-Sales

Research Design:

Appendix C: Interview Guide for Retail Stores, Wholesaler and FFP Processors

Research question 1:

Appendix D: Planning Environment Characteristics – Processing Stages

Appendix E: Planning Environment Characteristics – Case Studies

Research question 2:

Appendix F: Propositions for Demand and Supply Information Sharing

Appendix G: Real-Time Demand Information Sharing: Performance

Appendix H: Real-Time Demand Information Sharing: Test Results

Appendix I: Formulation of wSLE Forecasting Accuracy Measure and Test Results

Appendix J: Formulation of EWA_{3SL} Inventory Control Heuristic

APPENDIX A: PLANNING ENVIRONMENT CHARACTERISTICS - LITERATURE

Table A-1. Overview of relevant PECs in literature

Characteristic	Type	Description
Volume	D	number of products produced per year (Jonsson and Mattsson, 2003; Romsdal et al., 2014; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Type of procurement ordering	D	order by order procurement or blanket order release from a delivery agreement (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Demand type	D	demand from forecast, calculated requirements or from customer order allocations (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Time distributed demand	D	whether the demand is distributed over time or an annual figure (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Source of demand	D	whether demand is stock replenishment order or customer order (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Inventory accuracy	D	the extent to which there is accuracy in stock on hand data (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Demand-stimulating events	D	whether demand is stimulated by promotions, seasonality, product interrelation (Dreyer et al., 2018)
Availability requirements	D	whether products are expected to have constant availability or not (Dreyer et al., 2018; Ivert et al., 2015)
Demand frequency/ lumpiness	D	number of times per year products are ordered (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Customer service elements	D	inventory service levels, lead times, and delivery precision, quality and flexibility (Romsdal et al., 2014; Wänström and Jonsson, 2006)
Ramp-up level	D	the smoothness of the phase-in/out: gradually increased/decreased demand or a phase-in/out on a specific date (Wänström and Jonsson, 2006)

Characteristic	Type	Description
Demand uncertainty	D	the uncertainty of demand, measured as forecast accuracy or the coefficient of variation (CoV) (Ivert et al., 2015; Romsdal et al., 2014; Wänström and Jonsson, 2006)
Seasonality of supply	S	the extent to which there is seasonality in supply (Dreyer et al., 2018)
Supplier base complexity	S	number of suppliers per year, their geographical localisation, and supplier segments (Bozarth et al., 2009; Ivert et al., 2015) for the different products (Dreyer et al., 2018)
Multiple brands	S	number of different brands for the same type of product; (Dreyer et al., 2018)
Capacity constraints	S	the capacity constraints at processor (Dreyer et al., 2018)
Supplier service elements	S	inventory service levels, lead times, and delivery precision, quality, flexibility, etc. (Wänström and Jonsson, 2006)
Material supply scrap level	S	the percentage of materials supply chain batch that is scrapped (Wänström and Jonsson, 2006)
Type of procurement ordering	S	whether the order is by order procurement or blanket order releases from a delivery contract (Wänström and Jonsson, 2006)
Lot size	S	the typical lot size purchased (Wänström and Jonsson, 2006)
Long and/or unreliable supplier lead times	S	the degree to which supplier lead times are long and/or unreliable (Bozarth et al., 2009)
Number of suppliers	S	the number of suppliers to the given company/product (Bozarth et al., 2009)
Supply uncertainty	S	the predictability and variability in supply (Ivert et al., 2015)
BOM complexity	P	the number of levels in the bill of material and the typical number of items on each (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Product complexity and variety	P	the complexity of the product and existence of optional product variants (Dreyer et al., 2018; Ivert et al., 2015; Jonsson and Mattsson, 2003; Romsdal et al., 2014; Spenhoff et al., 2014)
Degree of value added at order entry	P	the extent to which the manufacturing of the products is finished prior to receipt of customer order (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Proportion of customer specific items	P	the extent to which customer specific items are added to the delivered product, e.g. the addition of accessories (Jonsson and Mattsson, 2003; Spenhoff et al., 2014) (Wänström and Jonsson, 2006)
Product/item value	P	the value of the item or product (Wänström and Jonsson, 2006)
Perishability and shelf life	P	whether products have finite or fixed lifetime (Dreyer et al., 2018; Ivert et al., 2015; Romsdal et al., 2014)
Product life cycle (PLC)	P	the product' stage in the life cycle (new/introduction, growth, maturiy, decline) (Romsdal et al., 2014)
Inter-relationships in demand among products	P	the extent to which there is inter-relationships in demand among products (Dreyer et al., 2018)
Shortening product life cycles	P	whether there are shortening product life cycles, more frequent new product introductions; (Dreyer et al., 2018)

Characteristic	Type	Description
Heterogeneity	P	the extent to which there is heterogeneity between the products (Dreyer et al., 2018)
Number of SKUs	P	the range of a company's product offering (Dreyer et al., 2018; Ivert et al., 2015)
The rate of change in the product portfolio	P	the number of product launches and removals per year (Ivert et al., 2015)
Batch size	PR	the typical manufacturing order quantity (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Through-put time	PR	the typical manufacturing through-put times of the products (Ivert et al., 2015; Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Number of operations	PR	the number of operations in typical routings (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Production lead time	PR	the product's production lead time; (Romsdal et al., 2014)
Volume flexibility	PR	the ability to handle the variability in demand volumes (Wänström and Jonsson, 2006)
Product mix flexibility	PR	the ability to handle the variability in demand between products in marketed product lines (Wänström and Jonsson, 2006)
Delivery flexibility	PR	the ability to handle the variability in open customer orders (Wänström and Jonsson, 2006)
Production network complexity	PR	the level of production network complexity; (Ivert et al., 2015)
Manufacturing strategy	PR	the type of manufacturing strategy (Ivert et al., 2015)
Production uncertainty	PR	the extent to which there is production uncertainty (Ivert et al., 2015; Romsdal et al., 2014)
Phase-in/out date	PR	whether there is a fixed date or a date that can be adjusted manually (Wänström and Jonsson, 2006)
MP method	PR	whether the planning is MRP, kanban, re-order point, fixed order interval, etc. (Wänström and Jonsson, 2006)
Planning frequency	PR	whether the planning is transaction based, daily or weekly planning (Wänström and Jonsson, 2006)
Planning periods	PR	whether the planning periods are bucketless, daily or weekly time buckets (Wänström and Jonsson, 2006)
Time fences	PR	specifies the periods in which various types of change can be dealt with (Wänström and Jonsson, 2006)

Note: Type: P = product, PR = production, S = supply, D = demand

APPENDIX B: EMPIRICAL STUDIES ON POINT-OF-SALES

Table B-2. Empirical POS data literature on demand forecasting and inventory control in grocery retailing context (Paper #9)

Author	RP&C field	Supply chain focus	Products	Information shared	Data dimensions	# of products	Aggregation	Decision-horizon
Ehrenthal et al. (2014)	IC	RS	Energy drink, milk, lettuce, sausage, eggs, caffeinated soda, croissants, cigarettes, potato chips, orange juice	Raw POS data	one-year POS data from one RS	1000	Product	One day review (over-lapping two days)
Hartzel and Wood (2017)	DF	MA ↔ (DC ↔) R	Mixed food products	Raw POS data, customer orders	60,651 orders for 10 months from 25 DCs	494	Summed orders	Short-term, weekly
Huber et al. (2017)	DF	DC ↔ RS	Bakery (buns and breads)	Raw POS data	18 months POS data from 6 RS	16	Product	Short term, daily
Jin et al. (2015)	DF	SU ↔ DC ↔ RS	Dry grocery products and fresh, refrigerated products with short shelf-lives	Week-level POS data, DC orders	104 observations for 104 weeks from six DCs and six RS	14	Products per week	Weekly and monthly

Author	RP&C field	Supply chain focus	Products	Information shared	Data dimensions	# of products	Aggregation	Decision-horizon
Narayanan et al. (2019)	DF	SU ↔ DC ↔ RS	Cereal adult, cereal children, detergent, cosmetics, pizza	POS data, orders	two years of daily POS data and three months of RS orders for each SKU and inventory stocking point from two DC and 271 RS	21	Product	Short term (R, mQ)
Williams and Waller (2010)	DF	DC ↔ RS	Cereal, canned soup and yogurt products	POS data, orders	Two years of weekly POS and order data	10	Product	Short-term, weekly
Williams and Waller (2011)	DF	DC	Ready-to-eat cereal products	POS data	Two years of weekly POS and order data from 18 DC and 180 RS	10	Product per RS	Short term, weekly
Williams et al. (2014)	IC	DC	Six dry grocery products	Week-level DC orders, POS data	110* weeks DC orders and POS data from one MA and nine retail DCs	6	Product	Short term,

* 104 weeks treated as in-sample, 6 weeks as out-of-sample

Note: RP&C field: IC = Inventory control, DF = demand forecasting
Supply chain focus: SU = supplier, MA = manufacturer, DI = distributor, DC = distribution centre, WH = wholesaler, R = retailer, RS = retail stores

APPENDIX C: INTERVIEW GUIDE FOR RETAIL STORES, WHOLESALER AND FFP PROCESSOR

Table B-3. Questions for semi-structured interviews with FFP processor (P), wholesaler (W) and retail stores (S)

Q#	P	W	S	Background
1	x	x	x	What is your position and area(s) of responsibility?
2	x	x	x	What experience do you have in retailing/grocery industry?
3	x	x	x	How long time have you been in the company?
4	x			How long time have you been supplier to the wholesaler?
5	x			Which markets/countries do you sell to?
6	x	x	x	How many customers/suppliers do you have and what types are they? (retail chains, wholesaler, catering etc.)
7	x	x	x	How is your customer/supplier portfolio geographically?
8			x	How many employees do you have in the store?
9			x	How many stores (from the same retail chain) are there in your city?
10	x			How many production facilities do you use for processing FFPs to wholesaler?
11	x			What is the lead-time from raw materials arrive until ready FFPs?
12		x		What is the lead-time from FFP arrive at warehouse until shipment?
13	x			Which production strategy(ies) do you use? (MTO, MTS, PTO, Mix etc.)
14	x			How many FFPs do you process annually of branded and private label? And for the wholesaler?
15		x		How many FFPs do you order annually of branded and private label?
16	x	x		How big is the variation in your product portfolio? (small, medium or large)
17	x	x		How often, and typically when, do you experience changes to the product assortment per year? And for how many products?
18	x			Please describe your production stability?
19	x			Please describe how you experience the wholesaler as a customer (big vs small, stable vs unpredictable etc.)
20		x		Please describe how you experience the suppliers (big vs small, stable vs unpredictable etc.)
21	x	x		How would you describe the collaboration with wholesaler/supplier? And in which areas does it work particularly well? Why?

Q#	P	W	S	Planning and scheduling of production/replenishments
22	x	x	x	Please describe the processing/replenishment planning process, including:
23	x	x	x	How, when and how often do you plan and schedule for future processing/replenishments - and for what time horizons?
24	x	x	x	What is your process for planning , including...
25	x	x	x	a. What steps and phases do you go through, for the different time horizons - and for what purpose (s)? Is there an official description?
26	x	x	x	b. At what level is the processing/replenishments planned and scheduled for the different time horizons? (e.g. individual, group or aggregate product level)
27	x	x	x	c. What inputs (incl. data / information) are used for the different planning steps / phases?
28	x	x	x	d. What outputs (incl. data / information) come from each planning step / phase?
29	x	x	x	e. When is the planning frozen without the possibility of change, for the different time horizons?
30	x	x		f. How flexible is your planning in relation to unforeseen events?
31	x			g. How flexible is your production in relation to unforeseen events?
32	x	x	x	h. For the different planning steps - to what extent is it possible to make changes to the ordered volume? And with what time horizons can changes be made?
33	x	x	x	i. For the different planning steps - to what extent is it possible to make changes to the delivery time? And with what time horizons can changes be made?
34	x	x	x	j. What are the most important decisions related to the planning and scheduling of the production/replenishments?
35	x	x	x	Do you forecast future processing/replenishment volumes for the various planning stages?
36	x	x	x	a. At what level do you forecast - and for what time horizons? (eg product, customer, market or total level)
37	x	x	x	b. What inputs (incl. data / information) are used in connection with forecasting?
38	x	x	x	c. To what extent do you collaborate with the wholesaler/FFP processor/retail stores on forecasting?
39	x	x		d. How are forecast (s) integrated into the planning and scheduling?
40	x	x	x	What is your process for ordering raw materials/FFPs, for the different time horizons?
41	x	x	x	a. How long into the future do you order raw materials/FFPs?
42		x	x	i. At what time during the day do you typically order FFPs?
43		x	x	ii. How many people are involved in ordering? And is it a specialized function?
44		x	x	iii. Do you have dedicated people for ordering? (i.e. same people every time)
45	x	x	x	b. How often are purchase orders reviewed / revised? And possibly, with whom?
46		x	x	i. Are there typically any changes between the first order and the final order? If so, what are the main reasons for this change?

47	x	x	x	c. How is the fill-rate from your suppliers (low, medium, high - constant or fluctuating)
48	x	x	x	d. Is the any variation in raw materials/FFPs - and if so, how is it characterized? (eg reduced/increased quality, fat content, size or weight)
49	x	x	x	i. What are the possible consequences of the variation?
50	x	x	x	ii. Does it fluctuate over the year / season / planning period?
51	x	x	x	How flexible are your suppliers in relation to unforeseen events?
52	x	x	x	For the different planning steps - to what extent is it possible for you make changes to the ordered volume with your suppliers? And with what time horizons can changes be made?
53	x	x	x	For the different planning steps - to what extent is it possible for you to make changes to the delivery time with your suppliers? And with what time horizons can changes be made?
54		x	x	Do you use simulation to evaluate different scenarios during the planning and scheduling?
55	x	x	x	For all the above questions, are there any differences for campaign vs normal demand?
Q#	**P**	**W**	**S**	**Information use/sharing**
56	x	x	x	What data/information do you use to make decisions in the planning and scheduling of production/replenishments?
57	x	x	x	What information (of the following) do you share and receive? - inventory level - waste - damaged/broken products - available/used space for displaying products in retail stores - available/used space in storage room in retail stores - historical sales/orders - normal/campaign sales price - campaign sales price - price sensitivity - demand forecast - (historical) information about previous campaigns/seasons - uncertainty in demand - cannibalization of products - placement of product in retail store - placement in campaign-brochure (e.g. front/back or middle-pages) - other: ________
58	x	x	x	From where and how do you get this data/information?
59	x	x	x	a. When do you retrieve the information - and how old is it when used?
60	x	x	x	What is the most important data/information for the decision-making process (inventory control, forecast, MRP, MPS)?
61	x	x	x	a. Is there any data / information inputs that is desired, but not available today? If so, which?
62	x	x	x	When and how do you transfer information to the receiver?
63	x	x	x	For all the above questions, are there any differences for campaign vs normal demand?
Q#	**P**	**W**	**S**	**FFPs close to expiration**
64		x		How many FFPs are sold at reduced price due to close to expiration?
65			x	Do you buy FFPs close to expiration with reduced price?

66			*x*	If so, why do you buy this type of FFPs?
67			*x*	If not, why and would you be interested in buying this type of FFPs?
68		*x*	*x*	How do you manage FFPs close to expiration?
69		*x*	*x*	How do determine the price reduction?
70		*x*	*x*	Is there a dedicated role/function for handling these products?
71		*x*	*x*	If ordering too many FFPs (risking waste), do you then sell the FFPs internally (to other stores)? Or immediately reduce price upon receiving? Or?
72		*x*	*x*	For all the above questions, are there any differences for campaign vs normal demand?
Q#	**P**	**W**	**S**	**Out-of-stock situations**
73		*x*	*x*	How often do you experience out-of-stock?
74		*x*	*x*	What do you experience as the most typical reason for out-of-stock?
75		*x*	*x*	Are there any differences for different demand or product types?
Q#	**P**	**W**	**S**	**Performance**
76	*x*	*x*	*x*	Do you measure the efficiency and precision of the planning and scheduling? If so, how and what KPIs are used?
77	*x*	*x*	*x*	Do you measure the accuracy of the forecast? If so, how and what errors do you use? (MAPE, MPE, RMSE, MSE, etc.)
78	*x*	*x*	*x*	Do you share any performance information with FFP processor/wholesaler/retail store?
79	*x*	*x*	*x*	Do you actively use the (historical) performance information when planning and scheduling?
80	*x*	*x*	*x*	For all the above questions, are there any differences for campaign vs normal demand?
Q#	**P**	**W**	**S**	**Development needs**
81	*x*	*x*	*x*	Please describe in what way and why the current RP&C works well
82	*x*	*x*	*x*	a. Are there any areas which you think could be even better and why?
83	*x*	*x*	*x*	b. To what extent would you be willing to share information with wholesaler?
84	*x*	*x*	*x*	c. How much information would you be willing to share with wholesaler?
85	*x*	*x*	*x*	What would the dream scenario be like?

Note: P = FFP processor, W = wholesaler, S = retail store

APPENDIX D: PLANNING ENVIRONMENT CHARACTERISTICS – PROCESSING STAGES

Figures are on the next pages!

Figure D-1. Planning environment characteristics at fish processor

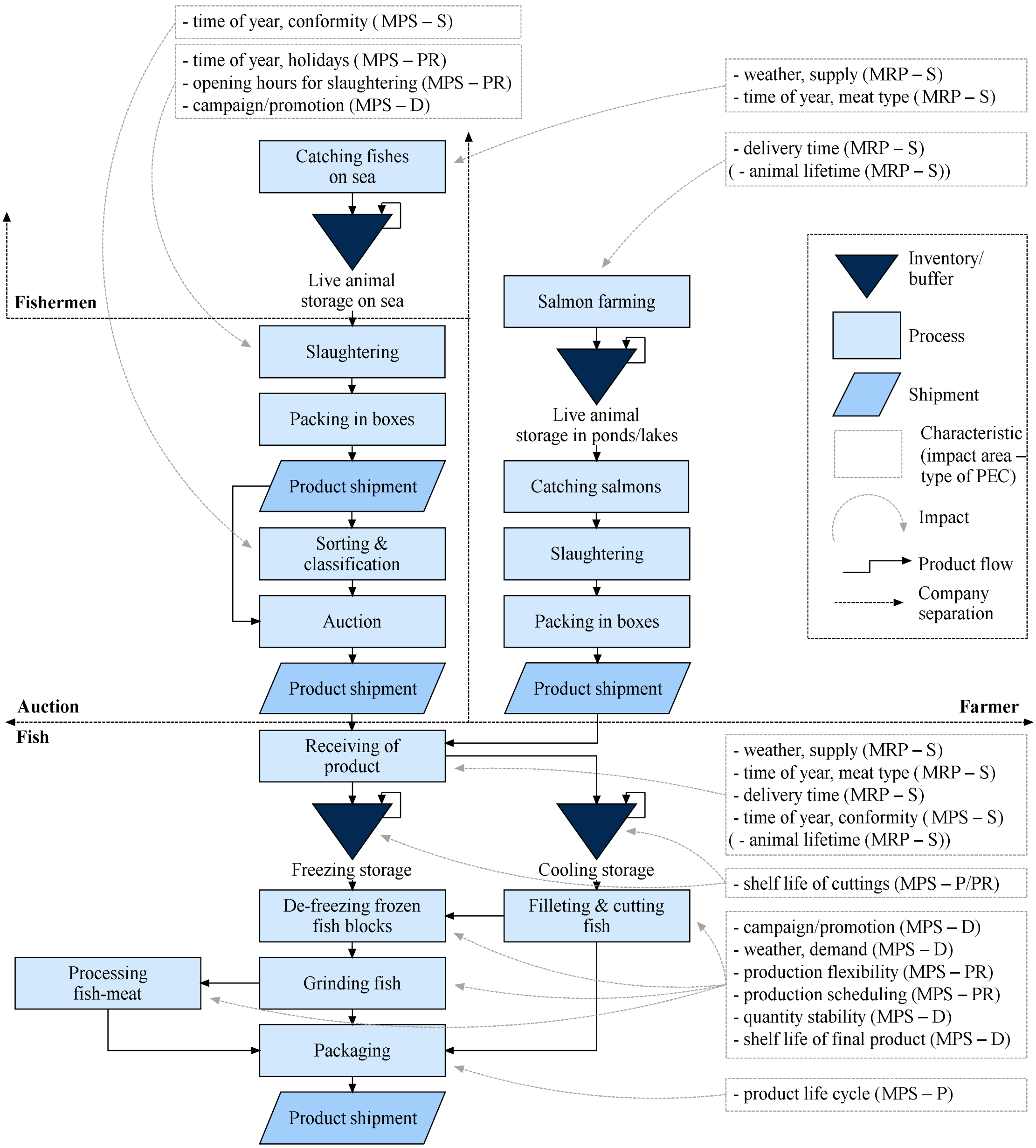


Figure D-2. Planning environment characteristics at chicken processor

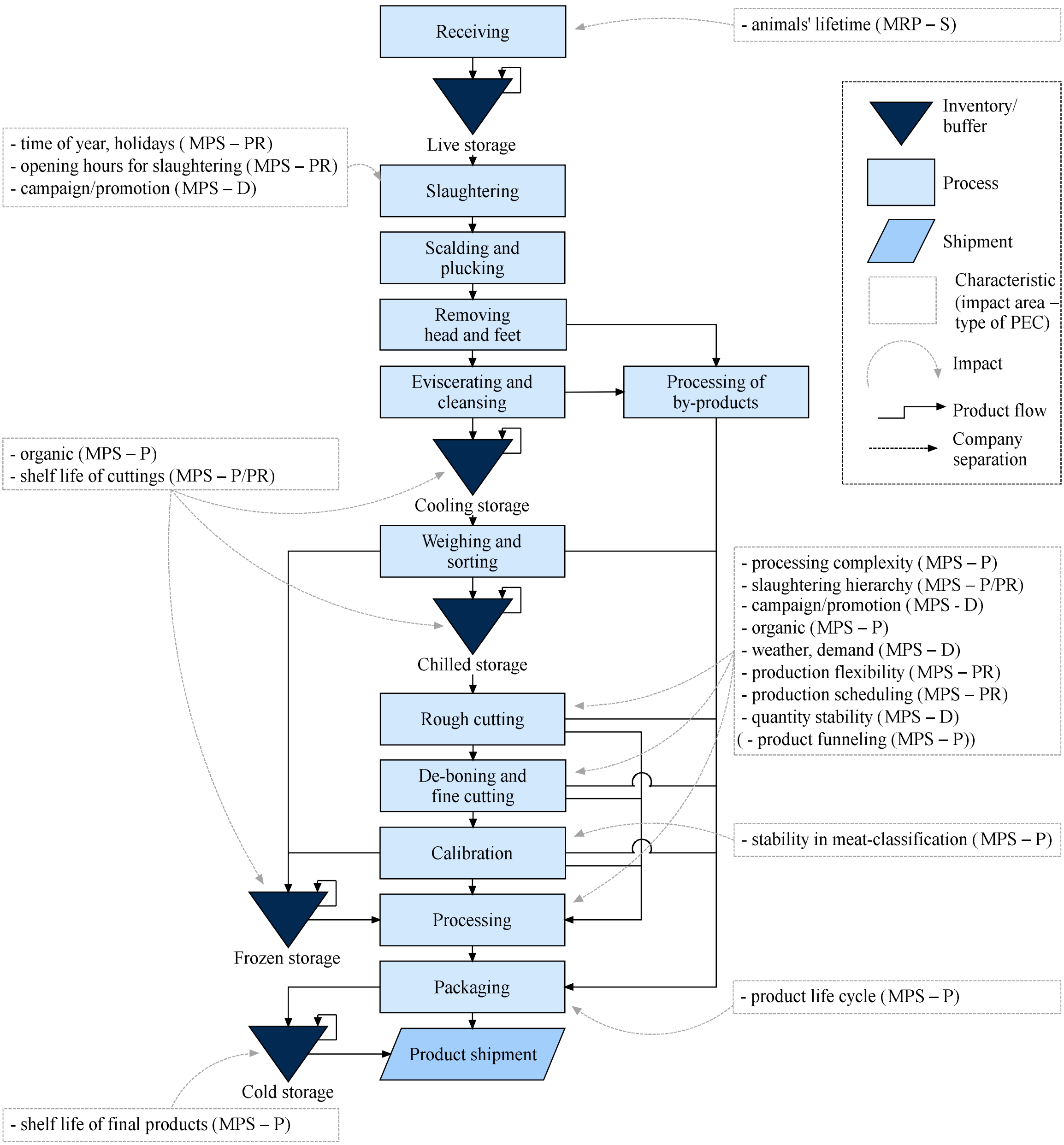
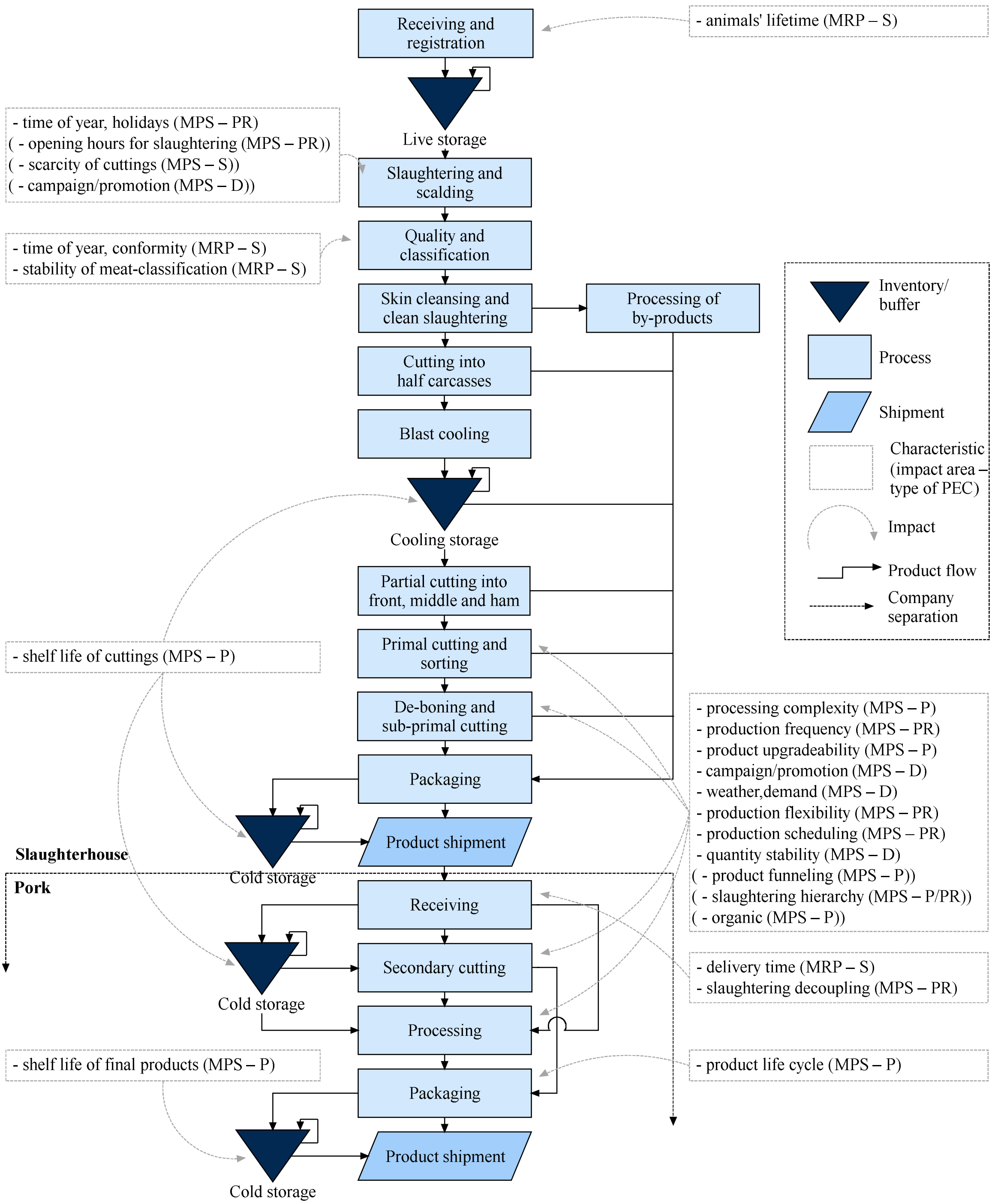


Figure D-3. Planning environment characteristics at pork processor



APPENDIX E: PLANNING ENVIRONMENT CHARACTERISTICS – CASE STUDIES

Table E-4. Planning environment characteristics impacting information sharing at processor, with identification of relevance per animal type (Christensen et al., 2020b)

PEC	Type	Description	Animal	Impact area
Ageing	P	Depending on primal/sub-primal/secondary cutting and intended level of ageing of the final product, the meat may be stored for ageing up to several months before ready for packaging.	B	MPS
Animal lifetime	S	Breeding time until slaughtering differs from animal to animal and meat type to meat type. Information should be shared accordingly to ensure enough number of animals for slaughtering.	B (P) C (F)	MRP
Campaign/ promotion	D	In case of campaigns/ promotions, additional amounts of raw materials are required and well as larger quantities to be produced and processed, in turn influencing processing start. Follows “the-larger-campaign, the-more-in-advance” principle.	B P C F	MRP/ MPS
Dairy prices	S	Rising milk prices cause farmers to keep cows alive for a longer time, thus reducing amounts sent to slaughtering, i.e. availability of beef meat.	B	MRP
Delivery time	S	Time to transport meat from origin place/country to processing facility. Information should be shared accordingly to ensure availability.	B* (P) F	MRP

PEC	Type	Description	Animal	Impact area
Import non-EU to EU	S	Import of non-EU meat to the EU is subject to GATT-quotas, restricting the amounts available in a year. The higher demand at the beginning of a period, the faster quotas are reached, resulting with variable and reduced availability	B**	MRP
Organic	P/S	For organic meat, available quantities are generally lower than for conventional, requiring that information sharing may be shared earlier to ensure building up temporary storage of meat (including vacuuming).	B** (P) C	MRP
Opening for slaughtering	PR	Depending on when the slaughterhouse is working during the week, then to supply raw material for processing and processing, information may be shared differently, e.g. if closed during weekend yet with daily deliveries to the wholesaler.	B (P) C	MPS
Quantity stability	D	If a product is required in the same quantity constantly, no need for information sharing arises.	B P C F	MPS
(Consecutive) processing capacity	PR	If the required capacity for a product/cutting in a given processing step exceeds max capacity in the preceding step, then the raw material is sourced from outside, requiring additional time.	B	MRP
Processing complexity	P	Based on if a product is, e.g. marinated or mixed, certain quantity restrictions may apply for processing the meat and producing the FFPs.	B P C	MPS
Processing flexibility	PR	Depending on how much processing can change in quantity, updated information about quantities may be shared	B P C F	MPS
Processing frequency	PR	Based on, e.g. internal scheduling, processing and shelf life, a product may be produced daily or only at different time points.	B P	MPS
Processing scheduling	PR	Depending on when the processing is scheduled (and re-scheduled), updating of information may be favourable.	B P C F	MPS

PEC	Type	Description	Animal	Impact area
Product funnelling	P	Depending on how many different FFPs can be made from a single meat cutting, different allowances for storing, ageing etc. applies.	B (P) (C)	MPS
Product life cycle	P	Depending on whether a product is, e.g. new or to be phased out, different time-horizons applies for ensuring enough amounts of packaging material and meat to meet demand.	B P C F	MRP/ MPS
Product upgradeability	P/PR	Depending on the extent to which a product may be downgraded (e.g. in terms of fat-%) influence scheduling of processing.	B P	MPS
Scarcity of cuttings	P/PR	Certain cuttings are only limited available in very few amounts per animal. This requires extra slaughtering immediately up to demand and (limited) stock building of meat-pieces.	B (P)	MPS
Shelf life of cuttings	P	The time that parts and cuttings can be stored before it must be processed ranges from, e.g. few days to more than one month, allowing small buffers to be built up for certain cuttings.	B (P) C F	MPS
Shelf life of final product	P	Depending on how short shelf life the final product has (days vs weeks vs months), buffers can be built up to meet fluctuations in demand.	B P C F	MPS
Short period demand	P	Certain cuttings are available throughout the year but only demanded during a short period. To meet demand, meat is, e.g. frozen from when demand ends and processes when the demand arises.	B	MRP
Slaughtering-decoupling	PR	Whether slaughtering and processing are inherently linked may influence the ability to source meat. If not linked, processing company may source meat pieces/cuts (according to specification) from multiple slaughterhouses, while if linked then what is available is pushed through processing.	B P	MRP
Slaughtering hierarchy	P/S/ PR	Depending on where a product is in the slaughtering hierarchy, it may be unique and only limited available from a carcass or common and "unlimited" available from a carcass mainly restricted by costs of meat (e.g. ground FFPs).	B (P) C	MPS

PEC	Type	Description	Animal	Impact area
Stability in meat-classification	P	Quality and conformity of the meat may generally fluctuate across animals letting availability of prime vs secondary quality meat become uncertain. The more fluctuating, the greater uncertainty for the availability of individual parts and cuts.	B (P) C	MRP
Time of year, conformity	S/ (PR)	Depending on the time of year, the animals are generally, e.g. more/less fat or larger/bigger, letting availability increase or decrease.	B (P) F	MRP
Time of year, holidays	PR	Depending on if around Christmas/ Easter/alike slaughtering and processing may start earlier than usual.	B P C F	MPS
Time of year, meat type	S	Depending on the time of year, certain meat types/breeds are excessive while others are scarce and vice versa.	B F	MRP
Weather, demand	D	The more unstable the weather is, the more increase in information sharing for weather-sensitive FFPs (e.g. grill sausages and steaks), hereunder both temperature, sun and humidity.	B P C F	MPS
Weather, supply	S	Depending on, e.g. wind and temperature (thereby also nutrition in water), the available amount of raw material may be reduced, influencing the available amount of raw material to source. The more unsteady weather, the more possible farmers to source from.	F	MRP

Note: Type: P = product, PR = production, S = supply, D = demand
Animal: B = beef, P = pork, C = chicken, F = fish
* = only for imported meat, ** = only for Beef2, ( ) = indirect impact

Table E-5. Planning environment characteristics impacting information sharing at the wholesaler and retail stores

PEC	Type	Description
Demand variation	D	The variation in demand reflected as the degree to which demand fluctuates through a given time period.
Shelf life	P	The number of days for which the FFP obtain an acceptable level of quality i.e. remains useable for further handling, fit for consumption or saleable. The shelf life reflects the level of deterioration (Kong and Singh, 2016; Robertson, 2016)
Supply lead-time	S	The time it takes from an animal is born until it is ready as a finished FFP, including growth, slaughtering and processing time.
Ordering frequency	D	The number of times an FFP is ordered influences the RP&C, since if an FFP is ordered frequently or even daily there is a relatively lower risk of waste compared to if ordered rarely (i.e. intermittent).
Substitution demand	D	The substituting FFP demand which is caused by the out-of-stock of another FFP. If "FFP A" is out-of-stock it may be substituted with "FFP B", causing extraordinary substitution demand on "FFP B" – and vice versa, depending on the products' positive and/or negative interdependence.
Substitution inventory	PR	The FFPs have asymmetrical financial losses[14] with increased food waste focus. Therefore, instead of buying too many "FFP B" (due to, e.g. minimum order quantities) which causes excess inventory and increased risk of waste from expiration, the available inventory from substituting "FFP A" may satisfy "FFP B"'s demand, thereby mitigate risk.
Price elasticity	D	The relative increase in demand caused by a certain price reduction. If "FFP A" is close to expiration, its price is reduced (in rounds) to minimize waste. The demand for the price reduced "FFP A" depends on the reduction, i.e. price elasticity, which influences the available inventory in different degrees.
Order fill-rate	S	FFPs to be delivered in the future, not yet in transit, may be influenced by (suddenly) reduced fill-rate due to factors such as e.g. sudden raw-material unavailability. This influences the safety stock, hence the ability to withstand variation in demand level, thus order-sizing of FFPs.
Demand type	D	The classification of demand as either total, normal, campaign or seasonal. Depending on whether the demand relates to normal, campaign or seasonal sales, different information sharing is required.

Note: Type: P = product, PR = production, S = supply, D = demand

[14] Too few products cause lost sales i.e. profit and thus a fraction of the total product costs. On the other hand, too many products cause price-reduction and/or deterioration i.e. lost purchase and handling costs and thus up to entire product costs.

APPENDIX F: PROPOSITIONS FOR DEMAND AND SUPPLY INFORMATION SHARING

Table F-6. Propositions for demand and supply information sharing (Christensen et al., 2020b)

Area	#	Description	Related PECs
Sourcing of raw material	P1a	For FFPs using raw materials with long predictable total supply lead-time, the wholesaler would benefit from sharing demand forecast for the entire supply/growth/ageing-period (content) with the FFP processor (direction) when the FFP processor forecasts demand (timing), followed by an update of the demand forecast when the FFP processor schedules and releases order(s). Because of predictable supply lead-time, the timing may be fixed (i.e. frequency).	ageing, animal lifetime, delivery time
	P1b	For FFPs using raw materials with short predictable total supply lead-time, the wholesaler would benefit from sharing demand forecast, if possible, even order, for the entire supply/growth-period (content) with the FFP processor (direction) when the FFP processor schedules and releases order(s) (timing). Since the supply lead-time is predictable, the timing may be fixed (frequency).	
	P1c	For FFPs using raw materials with unknown/stochastic total supply lead-time, the wholesaler would benefit from sharing demand forecast covering the need until next delivery (content) with the FFP processor (direction) when it obtains information about raw material availability and releases its order (timing). Since unknown/stochastic supply lead-time, timing is indefinable and not possible to schedule, thus the wholesaler shares upon request from the FFP processor (frequency).	
	P1d	In addition to P1c, for raw material acquired the same day as processing and/or delivery, the wholesaler	

Area	#	Description	Related PECs
		would benefit from sharing updated order information or retail store order (content) with the FFP processor (direction) when it sources raw material (timing). If overlapping retail stores opening hours, real-time retail store order (content) should be shared ongoingly (frequency) with order-determination upon FFP processor's request (timing) through (near-)real-time software such as internet (modality).	
Processing flexibility	P2	For FFPs with flexible processing quantities, the wholesaler would benefit from ongoingly (frequency) sharing real-time retail store order according to max tolerated deviations (content) with the FFP processor (direction) during the (adjustable) processing through (near-)real-time software such as internet (modality), with order-determination upon request from the FFP processor (timing).	processing complexity, product funnelling, product upgradeability, processing flexibility, processing scheduling, slaughtering hierarchy
Weather	P3a	For FFPs with weather sensitive demand in ongoing processing, the wholesaler would benefit from ongoingly (frequency) sharing real-time retail store order according to max tolerated deviations (content) with the FFP processor (direction) during the (adjustable) processing through (near-)real-time software such as, e.g. internet (modality), with order-determination upon request from the FFP processor (timing).	weather demand, weather supply
	P3b	For FFPs with weather sensitive demand not in ongoing processing, the wholesaler would benefit from sharing demand forecast (covering need until next delivery) (content) with the FFP processor (direction) when the FFP processor plans his processing (timing), followed by updated information when the FFP processor schedules the processing (frequency) – according to max tolerated deviations.	
	P3c	For FFPs with weather sensitive supply, the wholesaler would benefit from sharing updated demand forecast, or order, according to max tolerated deviations (content) with the FFP processor (direction) when he schedules and/or releases orders (timing). Qua P1c and P1d, information may represent real-time retail store order (content).	
Shelf life and undesired ageing	P4a	For FFPs with short shelf life which are processed daily and not yet in processing, the wholesaler would benefit from sharing demand forecast/order for the day, i.e. until next delivery according to retail store determined	ageing, processing frequency, shelf life of

Area	#	Description	Related PECs
		inventory levels (content) with the FFP processor (direction) when he schedules the processing (timing), followed by an update/order according to incoming retail store orders before processing starts (frequency).	cuttings, shelf life of final product
	P4b	For FFPs which are processed daily and in processing, the wholesaler would benefit from ongoingly (frequency) sharing real-time retail store orders (content) according to max tolerated deviations and retail store determined inventory levels (content) with the FFP processor (direction) with final order-determination upon request from the FFP processor (timing) through (near-) real-time software such as, e.g. internet (modality).	
	P4c	For FFPs with short shelf life which are processed daily and with daily access to additional raw material which are yet to be scheduled, the wholesaler would benefit from sharing aggregated retail store order (content) with the FFP processor (direction) when retail stores close/immediately before he schedules processing (timing), followed by update upon FFP processor's request qua P4b when in processing (frequency).	
	P4d	For FFPs with longer shelf life/ageing processed daily, the wholesaler would benefit from allowing minimum inventory-building to withstand demand fluctuations and smoothen out the FFP processor's processing, thereby share demand forecast (covering the next day' demand) (content) with the FFP processor (direction) when he schedules the processing (timing).	
	P4e	For FFPs with longer shelf life/ageing which are not processed daily, the wholesaler would benefit from sharing demand forecast (covering need until next delivery) (content) with the FFP processor (direction) when he plans the processing (timing), followed by updated order when he schedules the processing (frequency) – in accordance with max tolerated deviations.	
Enforced scarcity/ excess	P5a	For FFPs where raw material is subject to unknown and latent scarcity, the FFP processor would benefit from sharing information about available quantities of raw materials (content) with the wholesaler (direction) when either significant changes to availability occur so the wholesaler can plan demand forecast (content) and share with the FFP processor (direction). Or, if close to scarcity limits, when the wholesaler plans orders (content) and shares with the FFP processor (timing). This should be followed by an update when scheduling the orders (frequency).	processing capacity, campaign/pro motions, dairy prices, import non-EU to EU, opening for slaughtering, quantity stability, scarcity of cuttings,

Area	#	Description	Related PECs
	P5b	For FFPs where raw material is subject to unknown and sudden scarcity/excess, the FFP processor would benefit from sharing information about changes and projected available quantities of raw materials (content) with the wholesaler (direction) when the change occurs (timing), so the wholesaler can plan orders (content) and share with the FFP processor (direction), followed by an update when the wholesaler schedules orders (frequency).	slaughtering-decoupling, stability in meat classification, time of year conformity, time of year holidays, time of year meat type
	P5c	For FFPs with greater demand than processing capacity or raw material availability, the FFP processor would benefit from sharing information about available processing capacity or raw material availability (content) with the wholesaler (direction) when the wholesaler plans orders to the FFP processor (timing), so the wholesaler can plan and share orders and inventory levels accordingly (content) with the FFP processor (and potentially additional FFP processor) (direction). This should be followed by an update when scheduling the orders (frequency).	
	P5d	For FFPs subject to period(s) of unavailable processing capacity, the FFP processor would benefit from sharing information about this (content) with the wholesaler (direction) when either the periods are known to the FFP processor or the wholesaler plans orders to the FFP processor (timing), so the wholesaler can plan accordingly (content) with the FFP processor or an alternative FFP processor if needed (direction). This should be followed by an update when scheduling the orders (frequency).	
Special PECs	P6a	For FFPs with greater demand than raw material (adjustable) supply, the wholesaler would benefit from sharing demand forecast (content) with the FFP processor (direction) in accordance with supply lead-time - when facing a by-the-wholesaler-set significant chance of risking unavailability of raw material (timing), followed by an update when the wholesaler plans and/or schedules orders (frequency).	organic, product life cycle, short period demand
	P6b	For FFPs changing stage in the product life cycle, the wholesaler would benefit from sharing last expected demand date and demand forecast (content) with the FFP processor (direction) in accordance with a by-the-processor-set time point equal to supply lead-time (timing), followed by an update when the wholesaler plans and/or schedules orders (frequency).	

APPENDIX G: REAL-TIME DEMAND INFORMATION SHARING: PERFORMANCE RESULTS

Figure G-4. Mean value of median performance, campaign/normal demand (H1a, H1b, H2a and H2b) (Paper #9)

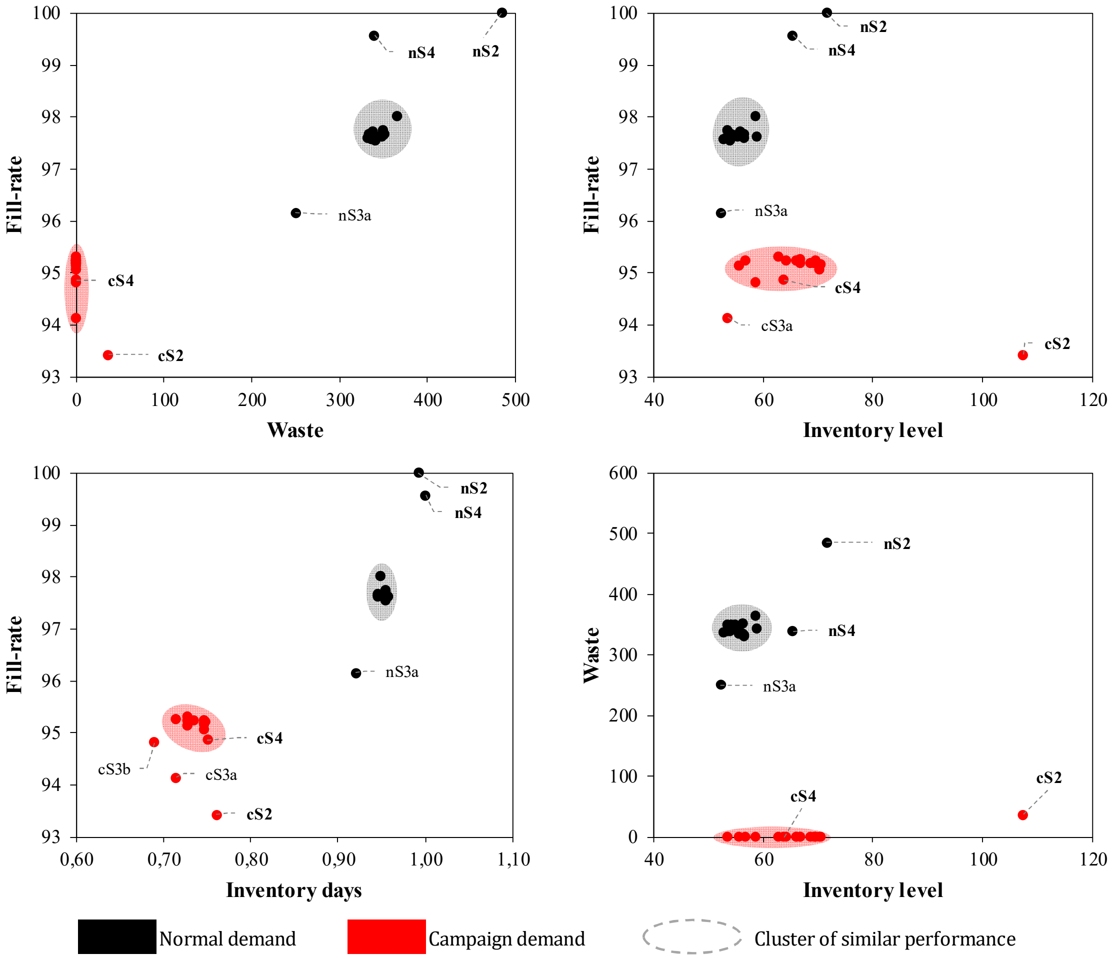


Figure G-5. Mean value of median performance, normal demand with processing method (H3a and H4a) (Paper #9)

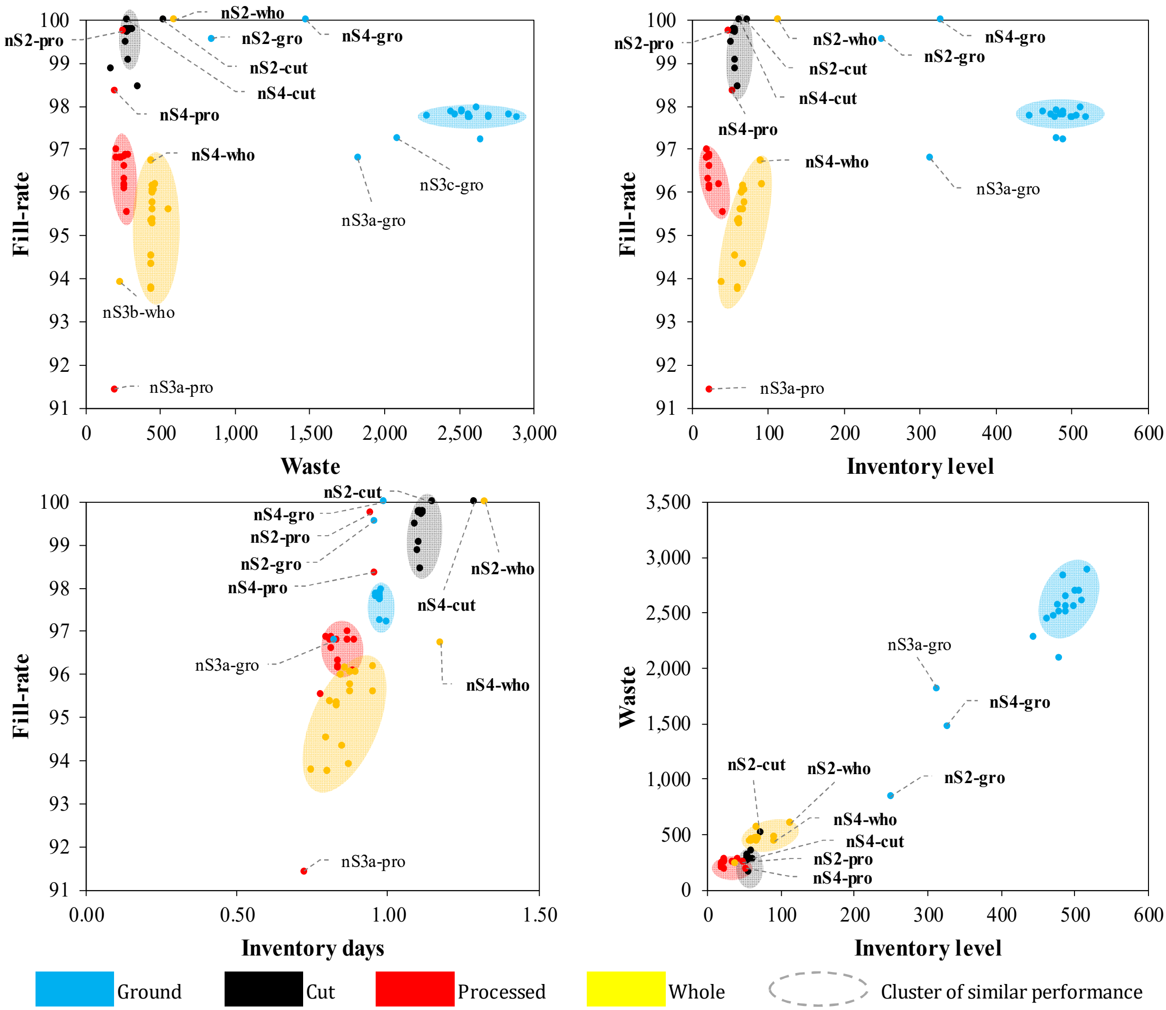
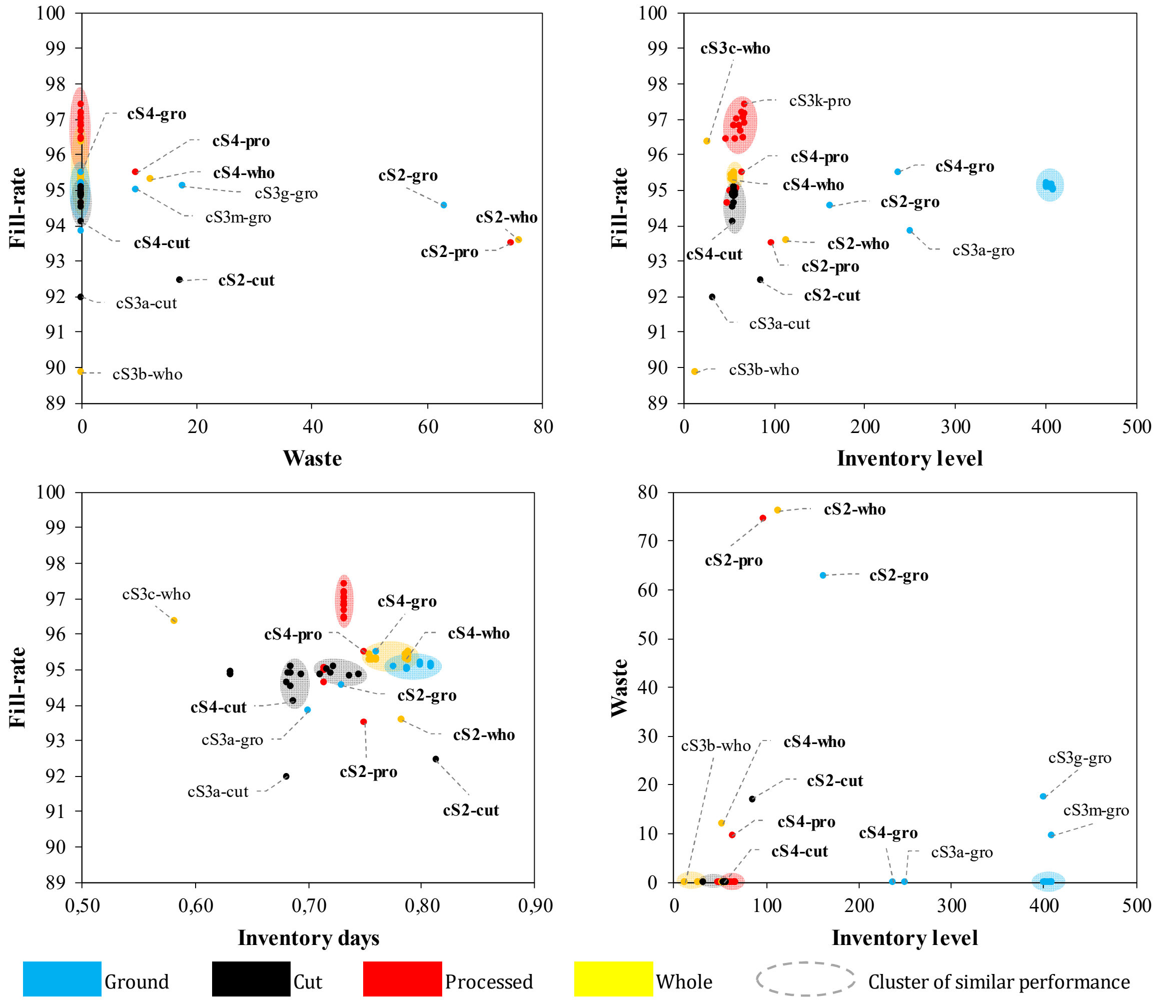


Figure G-6. Mean value of median performance, campaign demand with processing method (H3b and H4b) (Paper #9)



APPENDIX H: REAL-TIME DEMAND INFORMATION SHARING: TEST RESULTS

Tables are on the next pages!

Table H-7. Summarised statistical performance for S2, S3 and S4 scenarios, normal demand

	Scenario	Mean	SD	Median	IQ Range	95%	93%	90%	Skewness1	Skewnes2	Kurtosis
Fill-rate	S2: Baseline Forecast	98.56	2.89	100.00	1.20	100.00	100.00	100.00	-4,405.52	-75.78	150,123.40
	S3a 07:00-08:00	91.20	11.85	96.15	10.47	100.00	100.00	100.00	-1.70	-63.29	2.18
	S3b 07:00-09:00	94.71	10.32	97.64	4.89	100.00	100.00	100.00	-4.26	-43.01	20.86
	S3c 07:00-10:00	96.07	5.66	98.02	4.73	100.00	100.00	100.00	-2.35	-52.17	5.80
	S3d 07:00-11:00	96.38	4.76	97.64	4.72	100.00	100.00	100.00	-1.87	-40.00	3.48
	S3e 07:00-12:00	96.07	5.60	97.68	4.69	100.00	100.00	100.00	-2.03	-43.52	3.72
	S4: Differentiated sharing	97.20	5.85	99.57	2.46	100.00	100.00	100.00	-96.61	-61.58	1,566.62
Inventory level	S2: Baseline Forecast	145	183	72	172	487	403	327	2	61	5
	S3a 07:00-08:00	144	256	52	89	534	527	484	3	54	14
	S3b 07:00-09:00	166	280	59	138	607	495	425	3	58	13
	S3c 07:00-10:00	167	279	58	138	606	497	412	3	59	12
	S3d 07:00-11:00	167	280	55	139	615	502	414	3	61	12
	S3e 07:00-12:00	167	281	54	142	616	507	423	3	61	12
	S4: Differentiated sharing	150	206	65	135	540	416	399	2	62	5
Inventory days	S2: Baseline Forecast	1.2	0.7	1.0	0.4	2.4	2.2	1.9	2.9	52.9	11.7
	S3a 07:00-08:00	1.1	0.7	0.9	0.6	2.6	2.4	1.9	1.5	38.4	2.3
	S3b 07:00-09:00	1.1	0.6	1.0	0.5	2.4	2.0	1.5	1.7	39.1	3.6
	S3c 07:00-10:00	1.2	0.5	0.9	0.4	2.4	2.0	1.8	2.1	55.6	4.2
	S3d 07:00-11:00	1.2	0.6	0.9	0.5	2.4	2.2	1.9	1.8	55.2	3.0
	S3e 07:00-12:00	1.1	0.6	0.9	0.5	2.5	2.2	1.9	1.8	52.4	2.9
	S4: Differentiated sharing	1.3	0.8	1.0	0.5	2.6	2.5	2.3	2.7	51.7	9.5
Waste	S2: Baseline Forecast	819	1,023	485	887	3,169	3,005	2,437	2	49	2
	S3a 07:00-08:00	639	970	250	506	2,991	2,785	2,511	2	61	2
	S3b 07:00-09:00	809	1,180	345	677	3,444	3,085	3,035	2	60	2
	S3c 07:00-10:00	784	1,104	365	631	3,268	2,995	2,314	2	58	3
	S3d 07:00-11:00	838	1,188	349	716	3,629	3,274	2,560	2	62	2
	S3e 07:00-12:00	821	1,164	351	711	3,539	3,235	2,790	2	61	2
	S4: Differentiated sharing	758	1,124	340	660	3,694	3,166	2,244	2	56	3

Note: Skewness1 = Fisher-Pearson mean-based, Skewness2 = Pearson median-based

Table H-8. Summarised statistical performance for S2, S3 and S4 scenarios, campaign demand

	Scenario	Mean	SD	Median	IQ Range	95%	93%	90%	Skewness1	Skewnes2	Kurtosis
Fill-rate	S2: Baseline Forecast	91.87	6.85	93.43	11.47	100.00	100.00	99.72	-1.05	-28.94	1.33
	S3a 07:00-08:00	92.09	7.98	94.14	9.86	100.00	100.00	100.00	-1.52	-32.76	2.76
	S3b 07:00-09:00	92.67	7.76	94.81	8.19	100.00	100.00	100.00	-1.73	-35.18	3.79
	S3c 07:00-10:00	92.91	8.11	95.26	9.46	100.00	100.00	100.00	-1.89	-37.02	4.78
	S3d 07:00-11:00	93.00	8.09	95.15	10.04	100.00	100.00	100.00	-1.83	-33.99	4.47
	S3e 07:00-12:00	93.30	7.90	95.31	9.55	100.00	100.00	100.00	-1.83	-32.43	4.30
	S4: Differentiated sharing	93.43	7.25	94.87	7.51	100.00	100.00	100.00	-2.54	-25.33	9.17
Inventory level	S2: Baseline Forecast	137	111	107	123	374	324	300	1	34	1
	S3a 07:00-08:00	171	229	54	203	665	596	579	1	65	0
	S3b 07:00-09:00	203	267	59	320	699	649	625	1	69	1
	S3c 07:00-10:00	207	269	67	328	719	708	564	1	67	1
	S3d 07:00-11:00	205	269	55	326	730	706	554	1	71	1
	S3e 07:00-12:00	207	266	63	326	698	687	548	1	69	1
	S4: Differentiated sharing	159	182	64	210	529	504	445	1	66	1
Inventory days	S2: Baseline Forecast	0.8	0.2	0.8	0.2	1.1	1.0	1.0	0.6	6.7	1.7
	S3a 07:00-08:00	0.7	0.5	0.7	0.3	1.5	1.1	1.0	1.8	5.5	4.4
	S3b 07:00-09:00	0.8	0.5	0.7	0.5	1.9	1.3	1.1	1.5	17.9	2.4
	S3c 07:00-10:00	0.8	0.5	0.7	0.4	2.0	1.3	1.1	1.5	18.5	2.5
	S3d 07:00-11:00	0.8	0.5	0.7	0.4	1.9	1.3	1.1	1.4	15.9	2.4
	S3e 07:00-12:00	0.8	0.5	0.7	0.4	2.0	1.3	1.1	1.4	18.5	2.5
	S4: Differentiated sharing	0.8	0.4	0.8	0.3	1.2	1.1	1.1	1.8	11.6	5.0
Waste	S2: Baseline Forecast	105	202	37	119	341	322	307	4	43	18
	S3a 07:00-08:00	46	243	-	4	71	67	43	6	24	35
	S3b 07:00-09:00	91	401	-	3	250	128	75	5	29	30
	S3c 07:00-10:00	101	413	-	5	347	240	103	5	31	28
	S3d 07:00-11:00	99	411	-	2	350	225	103	5	31	28
	S3e 07:00-12:00	100	411	-	6	361	233	108	5	31	28
	S4: Differentiated sharing	64	193	-	37	235	196	154	5	42	26

Note: Skewness1 = Fisher-Pearson mean-based, Skewness2 = Pearson median-based

Table H-9. Summarised statistical performance for S2, S3 and S4 scenarios, total demand

	Scenario	Mean	SD	Median	IQ Range	95%	93%	90%	Skewness1	Skewnes2	Kurtosis
Fill-rate	S2: Baseline Forecast	95.82	5.97	98.22	3.26	100.00	100.00	100.00	-1.78	-61.05	2.39
	S3a 07:00-08:00	92.12	9.00	95.20	9.62	100.00	100.00	100.00	-1.72	-51.87	3.06
	S3b 07:00-09:00	94.43	9.76	96.71	5.30	100.00	100.00	100.00	-4.70	-35.44	25.57
	S3c 07:00-10:00	95.67	4.76	97.03	4.96	100.00	100.00	100.00	-1.44	-43.32	1.58
	S3d 07:00-11:00	95.84	4.59	97.07	4.36	100.00	100.00	100.00	-1.33	-40.55	1.04
	S3e 07:00-12:00	95.77	4.74	97.06	4.47	100.00	100.00	100.00	-1.31	-41.17	0.77
	S4: Differentiated sharing	96.56	4.82	98.09	3.00	100.00	100.00	100.00	-1.69	-48.12	1.59
Inventory level	S2: Baseline Forecast	141	165	71	164	458	393	331	2	64	4
	S3a 07:00-08:00	143	232	52	107	541	523	479	3	60	10
	S3b 07:00-09:00	165	255	56	166	624	522	396	3	65	9
	S3c 07:00-10:00	167	257	56	160	641	530	418	3	66	8
	S3d 07:00-11:00	167	258	52	164	653	535	420	3	68	8
	S3e 07:00-12:00	167	258	52	166	648	539	421	3	68	8
	S4: Differentiated sharing	147	192	62	156	555	422	402	2	68	4
Inventory days	S2: Baseline Forecast	1.2	0.7	1.0	0.4	2.3	2.1	1.9	3.2	48.3	13.3
	S3a 07:00-08:00	1.1	0.7	0.9	0.5	2.6	2.4	1.9	1.7	45.5	2.6
	S3b 07:00-09:00	1.0	0.6	0.9	0.4	2.3	2.0	1.5	1.9	37.8	3.9
	S3c 07:00-10:00	1.1	0.5	0.9	0.4	2.4	2.0	1.8	2.1	50.2	4.3
	S3d 07:00-11:00	1.1	0.6	0.9	0.5	2.4	2.1	1.9	1.9	50.7	3.0
	S3e 07:00-12:00	1.1	0.6	0.9	0.4	2.5	2.1	1.9	1.9	52.0	3.0
	S4: Differentiated sharing	1.2	0.8	1.0	0.5	2.6	2.4	2.2	2.8	47.9	10.2
Waste	S2: Baseline Forecast	907	1,134	561	863	3,416	3,136	2,445	2	46	4
	S3a 07:00-08:00	677	1,075	250	507	2,991	2,795	2,550	2	60	3
	S3b 07:00-09:00	886	1,402	345	692	3,533	3,204	3,077	2	58	7
	S3c 07:00-10:00	869	1,351	365	642	3,433	3,166	2,363	3	57	8
	S3d 07:00-11:00	921	1,418	351	720	3,633	3,429	2,595	2	61	7
	S3e 07:00-12:00	905	1,398	353	722	3,539	3,394	2,827	2	60	7
	S4: Differentiated sharing	812	1,234	348	696	3,940	3,345	2,244	2	57	4

Note: Skewness1 = Fisher-Pearson mean-based, Skewness2 = Pearson median-based

Table H-10. Summarised statistical performance for S2, S3 and S4 scenarios grouped by processing method, normal demand

Demand type	Processing method	Scenario	Inventory days	Inventory level	Fill-rate	Waste
Normal	Cut	nS2-cut	1.1	72	100.00	519
		nS3a-cut	1.1	56	98.87	168
		nS3b-cut	1.1	59	98.44	349
		nS3c-cut	1.1	55	99.07	289
		nS3d-cut	1.1	54	99.77	304
		nS3e-cut	1.1	54	99.78	316
		nS3f-cut	1.1	54	99.79	295
		nS4-cut	1.3	61	100.00	281
	Ground	nS2-gro	1.0	249	99.57	846
		nS3a-gro	0.8	313	96.80	1,821
		nS3b-gro	1.0	487	97.23	2,643
		nS3c-gro	1.0	479	97.25	2,090
		nS3d-gro	1.0	462	97.88	2,448
		nS3e-gro	1.0	498	97.75	2,562
		nS3f-gro	1.0	479	97.92	2,515
		nS4-gro	1.0	326	100.00	1,476
	Processed	nS2-pro	0.9	48	99.74	248
		nS3a-pro	0.7	22	91.43	192
		nS3b-pro	0.8	40	95.52	280
		nS3c-pro	0.8	34	96.20	258
		nS3d-pro	0.9	22	96.09	263
		nS3e-pro	0.8	20	96.31	258
		nS3f-pro	0.8	22	96.14	258
		nS4-pro	1.0	52	98.37	194
	Whole	nS2-who	1.3	113	100.00	600
		nS3a-who	1.0	92	96.18	469
		nS3b-who	0.9	39	93.89	233
		nS3c-who	1.0	67	95.59	559
		nS3d-who	0.9	68	94.32	441
		nS3e-who	0.8	60	93.75	442
		nS3f-who	0.7	61	93.77	441
		nS4-who	1.2	90	96.71	442

Table H-11. Summarised statistical performance for S2, S3 and S4 scenarios grouped by processing method, campaign demand

Demand type	Processing method	Scenario	Inventory days	Inventory level	Fill-rate	Waste
Campaign	Cut	cS2-cut	0.8	85	92.45	17
		cS3a-cut	0.7	32	91.99	-
		cS3b-cut	0.7	55	94.55	-
		cS3c-cut	0.7	55	95.09	-
		cS3d-cut	0.7	55	94.64	-
		cS3e-cut	0.6	55	94.86	-
		cS3f-cut	0.6	57	94.94	-
		cS4-cut	0.7	54	94.11	-
	Ground	cS2-gro	0.7	163	94.55	63
		cS3a-gro	0.7	250	93.85	-
		cS3b-gro	0.8	401	95.22	-
		cS3c-gro	0.8	407	95.16	-
		cS3d-gro	0.8	403	95.15	-
		cS3e-gro	0.8	402	95.14	-
		cS3f-gro	0.8	401	95.11	-
		cS4-gro	0.8	238	95.51	-
	Processed	cS2-pro	0.8	98	93.50	75
		cS3a-pro	0.7	52	94.97	-
		cS3b-pro	0.7	59	95.06	-
		cS3c-pro	0.7	49	94.63	-
		cS3d-pro	0.7	47	96.45	-
		cS3e-pro	0.7	56	96.83	-
		cS3f-pro	0.7	55	96.82	-
		cS4-pro	0.8	64	95.50	10
	Whole	cS2-who	0.8	114	93.56	76
		cS3a-who	0.8	54	95.39	-
		cS3b-who	0.4	13	89.84	-
		cS3c-who	0.6	27	96.34	-
		cS3d-who	0.8	56	95.41	-
		cS3e-who	0.8	55	95.41	-
		cS3f-who	0.8	56	95.50	-
		cS4-who	0.8	54	95.31	12

Table H-12. Summarised statistical performance for S2, S3 and S4 scenarios grouped by processing method, total demand

Demand type	Processing method	Scenario	Inventory days	Inventory level	Fill-rate	Waste
Total	Cut	tS2-cut	1.1	71	98.82	591
		tS3a-cut	1.1	53	97.05	191
		tS3b-cut	1.0	56	97.80	349
		tS3c-cut	1.0	52	97.51	289
		tS3d-cut	1.0	52	98.37	304
		tS3e-cut	1.0	52	98.42	316
		tS3f-cut	1.0	52	98.47	295
		tS4-cut	1.2	58	99.43	281
	Ground	tS2-gro	0.9	241	97.31	909
		tS3a-gro	0.8	298	95.21	1,821
		tS3b-gro	0.9	466	97.11	2,643
		tS3c-gro	0.9	465	97.21	2,270
		tS3d-gro	0.9	446	97.33	2,467
		tS3e-gro	0.9	484	97.28	2,574
		tS3f-gro	0.9	450	97.36	2,530
		tS4-gro	0.9	296	98.24	1,509
	Processed	tS2-pro	0.9	48	98.20	351
		tS3a-pro	0.7	25	92.01	192
		tS3b-pro	0.8	48	95.52	280
		tS3c-pro	0.8	39	96.11	258
		tS3d-pro	0.9	20	96.09	263
		tS3e-pro	0.8	19	96.36	258
		tS3f-pro	0.8	22	96.35	258
		tS4-pro	0.9	52	97.98	208
	Whole	tS2-who	1.1	113	97.57	801
		tS3a-who	0.9	84	95.47	469
		tS3b-who	0.8	32	92.12	233
		tS3c-who	0.9	59	91.57	564
		tS3d-who	0.8	66	94.93	447
		tS3e-who	0.8	65	94.79	447
		tS3f-who	0.8	67	94.59	446
		tS4-who	1.1	83	96.18	445

Table H-13. Impact in units and costs for median performance for S2, best S3 and S4 and scenarios grouped by processing method, total demand

Highest fill-rate from S2, S3 and S4	Fill-rate	Retail store demand	Out-of-stock	Lost revenue (EUR)	Waste-%	Waste	Lost revenue (EUR)	Total units lost	Total economic loss (EUR)	Saving compared to S2 (EUR)
tS2-cut	98.8%	2,217,483	26,173	2,787,577	0.3%	7,664	816,304	33,837	3,603,881	-
tS3g-cut	98.5%	2,217,483	32,984	3,513,029	0.2%	3,762	400,634	36,746	3,913,664	-309,783
tS4-cut	99.4%	2,217,483	12,532	1,334,730	0.2%	3,731	397,427	16,263	1,732,157	1,871,724
tS2-gro	97.3%	2,395,527	64,537	2,176,631	0.5%	11,410	384,817	75,947	2,561,448	-
tS3p-gro	97.6%	2,395,527	58,093	1,959,306	0.8%	18,869	636,404	76,963	2,595,710	-34,262
tS4-gro	98.2%	2,395,527	42,174	1,422,389	0.7%	16,033	540,733	58,206	1,963,122	598,327
tS2-pro	98.2%	1,375,028	24,757	608,274	0.3%	4,578	112,479	29,335	720,754	-
tS3p-pro	97.0%	1,375,028	41,394	1,017,041	0.2%	2,789	68,532	44,183	1,085,573	-364,820
tS4-pro	98.0%	1,375,028	27,735	681,454	0.2%	2,751	67,581	30,486	749,035	-28,282
tS2-who	97.6%	419,319	10,184	405,264	1.5%	6,132	244,016	16,316	649,280	-
tS3p-who	96.3%	419,319	15,696	624,621	0.9%	3,583	142,573	19,279	767,194	-117,915
tS4-who	96.2%	419,319	16,025	637,680	0.8%	3,524	140,218	19,548	777,898	-128,619

APPENDIX I:
FORMULATION OF WSLE FORECASTING ACCURACY MEASSURE AND TEST RESULTS

Formulation from Christensen et al. (2020a):
Weighted Shelf life Error (wSLE):

$$\mathrm{wSLE_q} = \frac{\sum_{\{t \in T | y_t \geq \hat{y}_{t,q}\}} \alpha |\hat{y}_{t,q} - y_t| + \sum_{\{t \in T | y_t < \hat{y}_{t,q}\}} \sum_{k=1}^{K-1} \left(\gamma_k \left(E_{t,s_k} - E_{t,s_{k+1}}\right) + \gamma_K E_{t,s_K}\right)}{\sum_{t=1}^{n} y_t}$$

where:

y_t = actual demand at time t and $\hat{y}_{t,q}$ is the forecasted demand at time t for quantile q
α = penalization value if $\hat{y}_{t,q} \leq y_{,t}$ i.e. under-forecasting
γ = penalization value if $\hat{y}_{t,q} > y_{,t}$ i.e. over-forecasting with penalties associated with the k price reductions of S, ranging from $\{\gamma_1, \dots, \gamma_K\}$ (see Figure 2)
S = the number of days until the price reduction k occurs with s_K i.e. the number of days until expiration, ranging from $\{s_1, \dots, s_K\}$ where $s_1 \leq s_2 \leq \dots \leq s_K$
$E_{t,s}$ = the inventory carried over to the day t+s, calculated as $\left(\hat{y}_{t,q} - C_{t,s}\right)^+$
$C_{t,s}$ = the cumulative demand for time t and the next s days
$\sum(\alpha + \gamma_1 + \gamma_2 + \dots + \gamma_K) = 1$ and $\gamma_1 + \dots + \gamma_{K-1} \neq \gamma_K$, since equal penalization of over-forecasting makes the weighted loss collapse to the qualtile loss function. Further, $\alpha \neq \gamma_1 + \dots + \gamma_K$, since equal penalization of over-/under forecasting makes the function collapse to conventional symmetrical penalization.

Table I-14. Performance results across all quantiles and products, wSLE scenario (Christensen et al., 2020a)

			Inventory/demand (%)				Waste (%)				Fill-rate (%)				Lost sales (%)			
#	**Measure**	**Model**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**
1	RMSE	ARIMA	21.4	24.5	28.7	35.0	4.9	5.1	5.4	5.9	96.3	97.0	97.6	98.3	3.7	3.0	2.4	1.7
	wMAPE	Combi (ARIMA/ETS/Theta)	**18.4**	**21.2**	**25.4**	**32.2**	**4.6**	**4.8**	**5.1**	**5.6**	95.6	96.4	97.2	98.2	4.4	3.6	2.8	1.8
	wQL	Seasonal naive	27.3	32.2	38.5	48.7	5.0	5.4	6.1	7.1	**96.8**	**97.8**	**98.8**	**99.4**	**3.2**	**2.2**	**1.2**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	**18.4**	**21.2**	**25.4**	**32.2**	**4.6**	**4.8**	**5.1**	**5.6**	95.6	96.4	97.2	98.2	4.4	3.6	2.8	1.8
2	RMSE	Combi (ARIMA/ETS/Theta)	**17.0**	**21.2**	**26.0**	**34.4**	**0**	**0**	**0.3**	**0.6**	95.5	96.3	97.0	97.8	4.5	3.7	3.0	2.2
	wMAPE	Combi (ARIMA/ETS/Theta)	**17.0**	**21.2**	**26.0**	**34.4**	**0**	**0**	**0.3**	**0.6**	95.5	96.3	97.0	97.8	4.5	3.7	3.0	2.2
	wQL	Moving Average	24.3	28.8	34.7	43.4	1.0	1.2	1.5	2.0	**96.6**	**97.2**	**97.7**	**98.4**	**3.4**	**2.8**	**2.3**	**1.6**
	wSLE	Combi (ARIMA/ETS/Theta)	**17.0**	**21.2**	**26.0**	**34.4**	**0**	**0**	**0.3**	**0.6**	95.5	96.3	97.0	97.8	4.5	3.7	3.0	2.2
3	RMSE	Combi (ARIMA/ETS/Theta)	**9.9**	**10.9**	**13.9**	19.8	**0**	**0**	**0**	**0**	97.4	98.0	98.6	99.3	2.6	2.0	1.4	0.7
	wMAPE	Combi (ARIMA/ETS/Theta)	**9.9**	**10.9**	**13.9**	19.8	**0**	**0**	**0**	**0**	97.4	98.0	98.6	99.3	2.6	2.0	1.4	0.7
	wQL	Moving Average	15.8	18.8	22.8	28.7	**0**	**0**	**0**	**0**	**98.2**	**98.8**	**99.4**	**99.8**	**1.8**	**1.2**	**0.6**	**0.2**
	wSLE	ETS	10.9	12.9	14.9	**18.8**	**0**	**0**	**0**	**0**	97.9	98.3	98.8	99.2	2.1	1.7	1.2	0.8
4	RMSE	Theta	19.0	22.5	27.0	33.5	0.1	0.2	0.4	0.6	98.0	98.5	98.8	99.3	2.0	1.5	1.2	0.7
	wMAPE	Theta	19.0	22.5	27.0	33.5	0.1	0.2	0.4	0.6	98.0	98.5	98.8	99.3	2.0	1.5	1.2	0.7
	wQL	Moving Average	24.5	29.0	34.5	43.5	1.0	1.3	1.7	2.5	**99.0**	**99.5**	**99.8**	**100**	**1.0**	**0.5**	**0.2**	**0**
	wSLE	ARIMA	-	-	-	**26.5**	-	-	-	**0.2**	-	-	-	98.8	-	-	-	1.2
		Combi (ARIMA/ETS/Theta)	**14.0**	**17.5**	**20.5**	**-**	**0**	**0**	**0**	-	97.0	97.9	98.4	-	3.0	2.1	1.6	-
5	RMSE	ARIMA	11.4	13.3	15.5	19.3	**0**	**0**	**0**	**0**	98.1	98.3	98.6	98.8	1.9	1.7	1.4	1.2
	wMAPE	Combi (ARIMA/ETS/Theta)	**11.0**	**12.1**	**14.4**	**18.2**	**0**	**0**	**0**	**0**	98.0	98.2	98.4	98.7	2.0	1.8	1.6	1.3
	wQL	Moving Average	14.4	17.0	20.5	25.8	**0**	**0**	0.1	0.1	**98.3**	**98.7**	**99.1**	**99.4**	**1.7**	**1.3**	**0.9**	**0.6**
	wSLE	ARIMA	11.4	-	-	-	**0**	-	-	-	98.1	-	-	-	1.9	-	-	-
		Combi (ARIMA/ETS/Theta)	-	**12.1**	**14.4**	**18.2**	-	**0**	**0**	**0**	-	98.2	98.4	98.7	-	1.8	1.6	1.3
6	RMSE	Theta	**13.4**	16.4	19.4	23.9	**0**	**0**	**0**	**0**	**97.4**	**98.0**	**98.5**	**99.1**	**2.6**	**2.0**	**1.5**	**0.9**
	wMAPE	Theta	**13.4**	16.4	19.4	23.9	**0**	**0**	**0**	**0**	**97.4**	**98.0**	**98.5**	**99.1**	**2.6**	**2.0**	**1.5**	**0.9**
	wQL	Theta	**13.4**	16.4	19.4	23.9	**0**	**0**	**0**	**0**	**97.4**	**98.0**	**98.5**	**99.1**	**2.6**	**2.0**	**1.5**	**0.9**
	wSLE	Combi (ARIMA/ETS/Theta)	**-**	**13.4**	**16.4**	**19.4**	-	**0**	**0**	**0**	-	97.3	98.0	98.7	-	2.7	2.0	1.3
		Theta	**13.4**	**-**	**-**	**-**	**0**	-	-	-	**97.4**	-	-	-	**2.6**	-	-	-

			Inventory/demand (%)				Waste (%)				Fill-rate (%)				Lost sales (%)			
#	Measure	Model	0.80	0.85	0.90	0.95	0.80	0.85	0.90	0.95	0.80	0.85	0.90	0.95	0.80	0.85	0.90	0.95
7	RMSE	Combi (ARIMA/ETS/Theta)	**24.1**	**27.6**	**37.9**	51.7	**0**	**0**	**0**	**0**	97.1	97.9	98.9	**99.8**	2.9	2.1	1.1	**0.2**
	wMAPE	Combi (ARIMA/ETS/Theta)	**24.1**	**27.6**	**37.9**	51.7	**0**	**0**	**0**	**0**	97.1	97.9	98.9	**99.8**	2.9	2.1	1.1	**0.2**
	wQL	Theta	27.6	34.5	41.4	51.7	**0**	**0**	**0**	**0**	**97.5**	**98.4**	**99.1**	99.8	**2.5**	**1.6**	**0.9**	0.2
	wSLE	ARIMA	-	-	-	**48.3**	-	-	-	**0**	-	-	-	99.7	-	-	-	0.3
		Combi (ARIMA/ETS/Theta)	**24.1**	**27.6**	**37.9**	-	**0**	**0**	**0**	-	97.1	97.9	98.9	-	2.9	2.1	1.1	-
8	RMSE	Combi (ARIMA/ETS/Theta)	**9.5**	**11.1**	**14.0**	**20.8**	**0**	**0**	**0**	**0**	96.8	97.4	98.1	98.8	3.2	2.6	1.9	1.2
	wMAPE	Combi (ARIMA/ETS/Theta)	**9.5**	**11.1**	**14.0**	**20.8**	**0**	**0**	**0**	**0**	96.8	97.4	98.1	98.8	3.2	2.6	1.9	1.2
	wQL	Moving Average	15.0	17.3	20.4	25.4	**0**	**0**	**0**	**0**	**97.8**	**98.4**	**98.9**	**99.4**	**2.2**	**1.6**	**1.1**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	-	-	**14.0**	-	-	-	**0**	-	-	-	98.1	-	-	-	1.9	-
		ETS	-	13.0	-	19.9	-	**0**	-	**0**	-	97.8	-	98.7	-	2.2	-	1.3
		Naive	13.0	-	-	-	**0**	-	-	-	97.7	-	-	-	2.3	-	-	-
9	RMSE	Combi (ARIMA/ETS/Theta)	**16.3**	**20.2**	**25.0**	**30.3**	**0.5**	**0.7**	**0.8**	**1.1**	97.0	97.8	98.7	99.4	3.0	2.2	1.3	0.6
	wMAPE	Combi (ARIMA/ETS/Theta)	**16.3**	**20.2**	**25.0**	**30.3**	**0.5**	**0.7**	**0.8**	**1.1**	97.0	97.8	98.7	99.4	3.0	2.2	1.3	0.6
	wQL	Theta	19.7	23.1	27.4	34.6	0.9	1.1	1.3	1.7	**97.8**	**98.5**	**99.1**	**99.7**	**2.2**	**1.5**	**0.9**	**0.3**
	wSLE	Combi (ARIMA/ETS/Theta)	**16.3**	**20.2**	**25.0**	**30.3**	**0.5**	**0.7**	**0.8**	**1.1**	97.0	97.8	98.7	99.4	3.0	2.2	1.3	0.6
10	RMSE	Theta	7.3	8.5	10.9	13.9	**0**	**0**	**0**	**0**	97.7	98.1	98.5	99.0	2.3	1.9	1.5	1.0
	wMAPE	Theta	7.3	8.5	10.9	13.9	**0**	**0**	**0**	**0**	97.7	98.1	98.5	99.0	2.3	1.9	1.5	1.0
	wQL	ARIMA	7.9	9.1	11.5	14.5	**0**	**0**	**0**	0.1	**97.5**	**98.1**	**98.6**	**99.1**	**2.5**	**1.9**	**1.4**	**0.9**
	wSLE	Combi (ARIMA/ETS/Theta)	**5.5**	**6.7**	**8.5**	**12.1**	**0**	**0**	**0**	**0**	97.1	97.4	98.0	98.8	2.9	2.6	2.0	1.2
11	RMSE	Combi (ARIMA/ETS/Theta)	**16.8**	**19.7**	**24.5**	**32.2**	**0.5**	**0.6**	**0.8**	**1.4**	97.0	97.7	98.4	98.9	3.0	2.3	1.6	1.1
	wMAPE	Combi (ARIMA/ETS/Theta)	**16.8**	**19.7**	**24.5**	**32.2**	**0.5**	**0.6**	**0.8**	**1.4**	97.0	97.7	98.4	98.9	3.0	2.3	1.6	1.1
	wQL	ARIMA	22.1	26.0	30.8	38.9	1.3	1.5	1.8	2.7	**98.1**	**98.6**	**99.1**	**99.4**	**1.9**	**1.4**	**0.9**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	**16.8**	**19.7**	**24.5**	**32.2**	**0.5**	**0.6**	**0.8**	**1.4**	97.0	97.7	98.4	98.9	3.0	2.3	1.6	1.1
12	RMSE	Theta	**24.7**	30.3	**37.1**	48.3	**2.1**	2.7	**3.6**	5.1	**98.0**	**98.9**	**99.6**	**100**	**2.0**	**1.1**	**0.4**	**0**
	wMAPE	Theta	**24.7**	30.3	**37.1**	48.3	**2.1**	2.7	**3.6**	5.1	**98.0**	**98.9**	**99.6**	**100**	**2.0**	**1.1**	**0.4**	**0**
	wQL	Theta	**24.7**	30.3	**37.1**	48.3	**2.1**	2.7	**3.6**	5.1	**98.0**	**98.9**	**99.6**	**100**	**2.0**	**1.1**	**0.4**	**0**
	wSLE	Combi (ARIMA/ETS/Theta)	-	**25.8**	-	-	-	**2.5**	-	-	-	97.7	-	-	-	2.3	-	-
		ETS	-	-	-	**44.9**	-	-	-	**5.1**	-	-	-	99.2	-	-	-	0.8
		Theta	**24.7**	-	**37.1**	-	**2.1**	-	**3.6**	-	**98.0**	-	**99.6**	-	**2.0**	-	**0.4**	-

			Inventory/demand (%)				Waste (%)				Fill-rate (%)				Lost sales (%)			
#	**Measure**	**Model**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**
13	RMSE	Combi (ARIMA/ETS/Theta)	**13.3**	**15.5**	**19.5**	26.5	**0**	**0**	**0**	**0**	95.1	95.9	**96.9**	**97.9**	4.9	4.1	**3.1**	**2.1**
	wMAPE	Combi (ARIMA/ETS/Theta)	**13.3**	**15.5**	**19.5**	26.5	**0**	**0**	**0**	**0**	95.1	95.9	**96.9**	**97.9**	4.9	4.1	**3.1**	**2.1**
	wQL	Combi (ARIMA/ETS/Theta)	**13.3**	**15.5**	**19.5**	26.5	**0**	**0**	**0**	**0**	95.1	95.9	**96.9**	**97.9**	4.9	4.1	**3.1**	**2.1**
	wSLE	ARIMA	-	17.3	-	**24.8**	-	**0**	-	**0**	-	**96.2**	-	97.8	-	**3.8**	-	2.2
		Combi (ARIMA/ETS/Theta)	-	-	**19.5**	-	-	-	**0**	-	-	-	**96.9**	-	-	-	**3.1**	-
		Theta	17.7	-	-	-	**0**	-	-	-	**96.1**	-	-	-	**3.9**	-	-	-
14	RMSE	Combi (ARIMA/ETS/Theta)	**17.2**	**18.8**	**21.9**	**28.1**	**0.4**	**0.5**	**0.7**	**0.9**	95.7	96.7	97.3	98.0	4.3	3.3	2.7	2.0
	wMAPE	Combi (ARIMA/ETS/Theta)	**17.2**	**18.8**	**21.9**	**28.1**	**0.4**	**0.5**	**0.7**	**0.9**	95.7	96.7	97.3	98.0	4.3	3.3	2.7	2.0
	wQL	Moving Average	20.3	23.4	26.6	32.8	0.6	0.8	1.0	1.5	**96.3**	**97.1**	**97.9**	**98.6**	**3.7**	**2.9**	**2.1**	**1.4**
	wSLE	Combi (ARIMA/ETS/Theta)	**17.2**	**18.8**	**21.9**	**28.1**	**0.4**	**0.5**	**0.7**	**0.9**	95.7	96.7	97.3	98.0	4.3	3.3	2.7	2.0
15	RMSE	ARIMA	**20.8**	**25.0**	**29.2**	**35.4**	**0**	**0**	**0**	0.1	96.9	97.7	98.4	99.1	3.1	2.3	1.6	0.9
	wMAPE	ARIMA	**20.8**	**25.0**	**29.2**	**35.4**	**0**	**0**	**0**	0.1	96.9	97.7	98.4	99.1	3.1	2.3	1.6	0.9
	wQL	ETS	22.9	27.1	31.3	39.6	**0**	**0**	**0**	**0**	**97.2**	**98.0**	**98.8**	**99.4**	**2.8**	**2.0**	**1.2**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	-	-	**29.2**	37.5	-	-	**0**	**0**	-	-	98.3	99.2	-	-	1.7	0.8
		ETS	22.9	27.1	-	-	**0**	**0**	-	-	97.2	98.0	-	-	2.8	2.0	-	-
16	RMSE	Combi (ARIMA/ETS/Theta)	**17.4**	**19.6**	**26.1**	39.1	**0**	**0**	**0**	0.2	96.4	97.3	98.4	**99.3**	3.6	2.7	1.6	**0.7**
	wMAPE	Moving Average	21.7	23.9	30.4	37.0	**0**	**0**	**0**	0.1	97.5	98.1	98.6	99.1	2.5	1.9	1.4	0.9
	wQL	Theta	21.7	23.9	28.3	37.0	**0**	**0**	**0**	0.1	**97.2**	**97.9**	**98.6**	99.3	**2.8**	**2.1**	**1.4**	0.7
	wSLE	ARIMA	-	-	-	**34.8**	-	-	-	0.2	-	-	-	99.1	-	-	-	0.9
		Combi (ARIMA/ETS/Theta)	-	**19.6**	**26.1**	-	-	**0**	**0**	-	-	97.3	98.4	-	-	2.7	1.6	-
		Moving Average	21.7	-	-	-	**0**	-	-	-	97.5	-	-	-	2.5	-	-	-
17	RMSE	ARIMA	45.9	56.8	70.3	89.2	1.1	1.4	2.0	3.0	99.8	99.9	100	100	0.2	0.1	0	0
	wMAPE	ARIMA	45.9	56.8	70.3	89.2	1.1	1.4	2.0	3.0	99.8	99.9	100	100	0.2	0.1	0	0
	wQL	ETS	40.5	48.6	56.8	**70.3**	1.0	1.3	1.7	**2.3**	98.8	99.1	99.4	99.7	1.2	0.9	0.6	0.3
	wSLE	Combi (ARIMA/ETS/Theta)	**29.7**	**37.8**	**51.4**	-	**0.6**	**0.8**	**1.6**	-	98.0	99.2	99.7	-	2.0	0.8	0.3	-
		ETS	-	-	-	**70.3**	-	-	-	**2.3**	-	-	-	99.7	-	-	-	0.3

APPENDIX J: FORMULATION OF EWA3SL INVENTORY CONTROL HEURISTIC

Formulation from Christensen et al. (2020):
To ensure simplicity in presentation, the available inventory is first defined as in equation (J1). For product p_1 at time t current inventory level is considered (on hand and in transit), plus all quantities ordered but not yet received/in transit multiplied by the fill-rate (β) for each supplier (l), minus already reserved quantities[15], within the review- (R) and lead-time (L) for i (Silver et al., 1998). Then, the estimated outdated (i.e. expired) quantities and estimated quantities sold at reduced price (due to close to expiration) up until the immediate prior time period are subtracted. For quantities sold at reduced price, there may be products with different expiration dates, i.e. different price-reduced quantities each day as identified by ε.

$$\mathrm{I}_{\mathrm{p}_1,\mathrm{t}}^{\text{available}} = \mathrm{I}_{\mathrm{p}_1,\mathrm{t}} + \sum_{\mathrm{i}=\mathrm{t}+1}^{\mathrm{R}_{\mathrm{p}_1}+\mathrm{L}_{\mathrm{p}_1}} \sum_{\mathrm{l}=1}^{\mathrm{S}_1 \rightarrow \mathrm{S}_\mathrm{x}} \mathrm{Q}_{\mathrm{p}_1,\mathrm{i},\mathrm{l}}^{\text{ordered}} \beta_{\mathrm{p}1,\mathrm{i},\mathrm{l}} - \sum_{\mathrm{i}=\mathrm{t}+1}^{\mathrm{R}_{\mathrm{p}_1}+\mathrm{L}_{\mathrm{p}_1}} \mathrm{Q}_{\mathrm{p}_1,\mathrm{i}}^{\text{reserved}} - \sum_{\mathrm{i}=\mathrm{t}+1}^{\mathrm{R}_{\mathrm{p}_1}+\mathrm{L}_{\mathrm{p}_1}-1} \widehat{\mathrm{Q}}_{\mathrm{p}_1,\mathrm{i}}^{\text{outdated}} - \sum_{\mathrm{i}=\mathrm{t}+1}^{\mathrm{R}_{\mathrm{p}_1}+\mathrm{L}_{\mathrm{p}_1}-1} \sum_{\mathrm{k}=1}^{\varepsilon_{\mathrm{p}_1}} \widehat{\mathrm{Q}}_{\mathrm{p}_1,\mathrm{i},\mathrm{k}}^{\text{reduced}} \tag{J1}$$

$\mathrm{I}_{\mathrm{p}_1,\mathrm{t}}$ = starting inventory position, after expired products are subtracted
$\mathrm{Q}_{\mathrm{p}_1,\mathrm{i},\mathrm{l}}^{\text{ordered}}$ = number of product p_1 already ordered but arriving later, within review time
$\beta_{\mathrm{p}1,\mathrm{i},\mathrm{l}}$ = fill-rate on ordered quantities of product p_1 from supplier l ($\mathrm{S}_1 \rightarrow \mathrm{S}_\mathrm{x}$)
$\mathrm{Q}_{\mathrm{p}_1,\mathrm{i}}^{\text{reserved}}$ = number of product p_1 reserved from inventory due to e.g. campaign or customer
$\widehat{\mathrm{Q}}_{\mathrm{p}_1,\mathrm{i}}^{\text{outdate}}$ = estimated number of product p_1 to expire within review time
$\widehat{\mathrm{Q}}_{\mathrm{p}_1,\mathrm{i},\mathrm{l}}^{\text{reduced}}$ = estimated number of product p_1 sold a reduced price within review time
$\varepsilon_{\mathrm{p}_1}$ = price elasticity of product p_1 for price reduction when p_1 gets close to expiration

[15] Customer orders placed long time in advance, e.g. pre-orders for campaigns.

In step 1 (Equation J2, below) in the EWA$_{3SL}$, if the available inventory of product p_1 at time t is less than the sum of expected demand within the review- and lead-time, the safety stock and the expected substitution-demand from other products (not having sufficient inventory) (product *2* to *x*, $p_2 \rightarrow p_x$), then continue to step 2. $E\left[D_{j,i}^{sub}\right]$ is expected substitution demand for all products p_j, when product p_1 has excess inventory and p_j has too low inventory to satisfy demand and thus substitute with product p_1. This is influenced by the substitution probability factor $\mu_{p_1|j}$ for all *j* products (Hübner, 2011). Similarly, when the substituting products p_j have excess inventory, allowing substituting demand from product p_1. In the formula we account for an FFP may have several other substituting FFPs as the case of e.g. multiple brands (brand#1, brand#2 and private label). For expected demand, this may be particularly relevant when a certain product may not be available from supplier for a (longer) period. This is depicted in Equation (J2).

In step 2 (equation J3), the substituting inventory available from product $p_2 \rightarrow p_x$ is included when evaluating against product $p_1$demand and product $p_2 \rightarrow p_x$ substitution demand. If the total available inventory is less than total expected demand, proceed to step 2a. Here the evaluation of safety stock and outdated/price-reduced products determines the order-size as described by (Kiil et al., 2018b). In the EWA$_{3SL}$, the number of products price-reduced due to close to expiration is additionally added as well as the substituting demand from other products if safety stock is smaller than the two. This is depicted in equations (J3-J7).

In step 3, if the available inventory is larger or equal to expected product and substitution demand, no order should be placed. This may be of particular relevance if experiencing too high inventory levels of substituting products that need to be reduced. Depending on the substitutability, different products inventories may be included in the calculation. Thus, EWA$_{3SL}$ includes risk mitigation by evaluating with substitution inventory that could otherwise end up as potential waste if inventory levels are high. This is depicted in equation (J8).

EWA$_{3SL}$ heuristic

1) If:

$$\mathrm{I}_{\mathrm{p_1},\mathrm{t}}^{\mathrm{available}} < \sum_{\mathrm{i}=\mathrm{t}+1}^{\mathrm{R_{p_1}}+\mathrm{L_{p_1}}} \mathrm{E}\left[\mathrm{D}_{\mathrm{p_1},\mathrm{i}}\right] + \mathrm{SS}_{\mathrm{p_1}} + \sum_{\mathrm{j}=1}^{\mathrm{p_2}\rightarrow\mathrm{p_x}} \sum_{\mathrm{i}=\mathrm{t}+1}^{\mathrm{R_{p_1}}+\mathrm{L_{p_1}}} \mathrm{E}\left[\mathrm{D}_{\mathrm{j,i}}^{\mathrm{sub}}\right]\mu_{\mathrm{p_1|j}} \tag{J2}$$

where:

$$\mathrm{D}_{\mathrm{j,i}}^{\mathrm{sub}} = 0 \quad \text{if} \quad \mathrm{I}_{\mathrm{j,i}}^{\mathrm{available}} \geq \mathrm{D}_{\mathrm{j,i}} \;\; \text{and} \;\; \mathrm{D}_{\mathrm{j,i}}^{\mathrm{sub}} > 0 \quad \text{if} \quad \mathrm{I}_{\mathrm{j,i}}^{\mathrm{available}} < \mathrm{D}_{\mathrm{j,i}}$$

$$\mu_{p_x|j} = \begin{pmatrix} 0 & \mu_{p_1 2} & \cdots & \mu_{p_1 j} & \cdots \\ \mu_{p_2 1} & 0 & \cdots & \mu_{p_2 j} & \cdots \\ \vdots & \vdots & \ddots & \vdots & \cdots \\ \mu_{p_x 1} & \mu_{p_x 2} & \cdots & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

then,

for all $I_{p_x,t}^{available} < E\left[D_{p_x,i}\right]$,

2) if,

$$\mathrm{I}_{p_1,t}^{available} + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{I}_{j,i}^{sub.avail.} < \sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{E}\left[\mathrm{D}_{p_1}\right] + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{E}\left[\mathrm{D}_{j,i}^{sub}\right] \mu_{p_1|j} \tag{J3}$$

then,

2a) if,

$$\mathrm{SS}_{p_1} < \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \widehat{\mathrm{Q}}_{p_1,i}^{outdated} + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{l=1}^{\varepsilon_{p_1}} \widehat{\mathrm{Q}}_{p_1,i,l}^{reduced} \tag{J4}$$

then,

$$\mathrm{Q}_{p_1,t} = \max\left(\left(\begin{array}{c} \displaystyle\sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{E}\left[\mathrm{D}_{p_1}\right] + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \widehat{\mathrm{Q}}_{p_1,i}^{outdated} + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{l=1}^{\varepsilon_{p_1}} \widehat{\mathrm{Q}}_{p_1,i,l}^{reduced} \\ \displaystyle + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{E}\left[\mathrm{D}_{j,i}^{sub}\right] \mu_{p_1|j} - \mathrm{I}_{p_1,t}^{available} \end{array}\right), 0\right) \tag{J5}$$

2b) if,

$$\mathrm{SS}_{p_1} \geq \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \widehat{\mathrm{Q}}_{p_1,i}^{outdated} + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{l=1}^{\varepsilon_{p_1}} \widehat{\mathrm{Q}}_{p_1,i,l}^{reduced} \tag{J6}$$

then,

$$\mathrm{Q}_{p_1,t} = \max\left(\left(\sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{E}\left[\mathrm{D}_{p_1,i}\right] + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} \mathrm{E}\left[\mathrm{D}_{j,i}^{sub}\right] \mu_{p_1|j} + \mathrm{SS}_{p_1} - \mathrm{I}_{p_1,t}^{available}\right), 0\right) \tag{J7}$$

for all $I_{p_x,t}^{available} \geq E\left[D_{p_x,i}\right]$,

3) if,

$$I_{p_1,t}^{available} + \sum_{j=1}^{p_2 \rightarrow p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} I_{j,i}^{sub.avail.} \geq \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{p_1}\right] + \sum_{j=1}^{p_2 \rightarrow p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{j,i}^{sub}\right] \mu_{p_1|j} \qquad (J8)$$

then,

$$Q_{p_1,t} = 0$$

$I_{p_1,t}^{available}$ = inventory position (on hand plus in transit) at time t for product p_1
$I_{j,i}^{sub.avail.}$ = beginning inventory at time i for substituting product j ($p_2 \rightarrow p_x$)
$\widehat{Q}_{p_1,i}^{outdate}$ = estimated number of product p_1 to expire within review time
$\widehat{Q}_{p_1,i,l}^{reduced}$ = estimated number of product p_1 sold a reduced price within review time
$E\left[D_{j,i}^{sub}\right]$ = expected substitution demand from product j ($p_2 \rightarrow p_x$)
$E\left[D_{p_1,i}\right]$ = expected demand from product p_1
SS_{p_1} = safety stock for product p_1
$Q_{p_1,t}$ = order quantity for product p_1
$\mu_{p_1|j}$ = substitution matrix for product j ($p_2 \rightarrow p_x$) substituting with product p_1 when $I_{j,i}^{available} < D_{j,i}$
ε_{p_1} = price elasticity of product p_1 for price reduction when p_1 gets close to expiration

APPENDED PAPERS

Research question 1:

Paper 1: "Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime."

Paper 2: "Information Sharing for Replenishment Planning and Control in Fresh Food Supply Chains: A Planning Environment Perspective."

Paper 3: "Replenishment Planning of Fresh Meat Products: Case Study from a Danish Wholesaler."

Paper 4: "Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration."

Paper 5: "Horizontal Integration in Fresh Food Supply Chain."

Research question 2:

Paper 6: "Developing New Forecasting Accuracy Measure Considering Product's Shelf Life: Effect on Availability and Waste."

Paper 7: "Product Characteristics for Differentiated Replenishment Planning of Meat Products."

Paper 8: "Managing Perishable Multi-Product Inventory with Supplier Fill-Rate, Price Reduction and Substitution"

Paper 9: "Real-Time Point-of-Sales Information Sharing in Fresh Food Supply Chain"

PAPER #1

Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime

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The PhD student defined the problem and proposed the structure and core scientific idea to solve it. The PhD student derived key-methodology, conducted case-study research and interviews, collected and analysed data, wrote the entire draft version of the paper, and re-vised it according to co-authors comments.

Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime

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Abstract. Demand and supply chain planning of meat products with short shelf life is studied in a Danish wholesaler case. Main findings are that the lifetime of animals influences information sharing in planning, and differentiating planning according to demand characteristics influence supply chain negatively. This study suggests lifetime-dependent differentiation in timeliness and frequency in sharing of information to enhance supply chain effectiveness and efficiency.

Keywords: Differentiation · Animal lifetime · Fresh meat · Demand planning

1. Introduction

Due to meat products' short shelf life, the risk of waste from expired products, due to poor planning and derived stock building, is large [1]. Meat products have a time-dependent scarcity, as their raw materials (i.e. animals) have different time between birth and slaughtering/catching. Since fresh meat products are unfit for storing, and high availability influences consumer loyalty [2], efficient, effective and differentiated demand and supply chain planning is paramount. In particular for wholesaler, linking shops with upstream supply chain by consolidating and balancing the converging and diverging demand and supply flow.

Current planning frameworks tends to focus on information sharing between the producer and customer [3], and, internal planning at product group level [4–6], differentiated through forecasting-, production strategy- and/or inventory management-oriented segmentation [7] (e.g. order characteristics (lead-time, shelf life, temperature etc.) and demand characteristics (seasonality, fluctuation, frequency etc.) [7–11]). This influences wholesaler' effectiveness and efficiency inappropriately. Since wholesaler has no control of producing the products [11], the products have short time from order dispatch to order arrival and are unsuitable for storing, and, the raw materials have large differences in growth time, there are the different requirements to timeliness and frequency of information sharing. The second largest discount retail chain in Denmark and its wholesaler operates with hundreds of different meat products, segmented only per demand characteristics. It is thus relevant to investigate how demand and supply chain planning could differentiate and what is its effect on information sharing and frequency. By comparing wholesaler's planning approach against different raw materials' lifetime, it is possible to identify how demand and supply chain planning should include the differentiating aspects. Focus is on fresh meat products with up to 14 days shelf life. The following presents this study' framework about animal lifetime and demand planning time-horizon, then methodology, case study, analysis, discussion and conclusion.

2. Theoretical Background

Demand and supply chain planning aims to predict the future demand and supply, and respond upon this by sharing information and initiating different upstream activities accordingly and timely, to effectively and efficiently meet demand instantly when occurring [11, 12]. Particularly for meat products, understanding demand and sharing information timely is needed due to the bullwhip effect [13] and constant degradation.

A key factor for improving supply chain operations is improving forecasting [14], which in turn creates a cost-effective supply chain [15]. For this purpose, products are usually grouped according to demand characteristics (e.g. steady, seasonal and promotional) with different efforts needed in forecasting and levels of supply chain collaboration [14]. The accuracy of forecasting is affected by time-horizon to forecast. The shorter time-horizon, the greater accuracy and reliability, hence, the lower risk and errors [8]. However, fresh meat products are influenced by scarcity after a certain point in time (i.e. when time to produce raw materials for slaughtering exceeds the forecast horizon). Hence, demand planning must be closely related with supply planning, since raw materials are living animals with different growth time. Table 1 shows the time it takes to grow different animals ready for slaughtering/catching, according to Danish Agriculture and Food Council. Clearly, the different meat types differ, from growth time of around one month for chickens to more than 24 months for beef, to catching fish according to size (influenced by nature and climate).

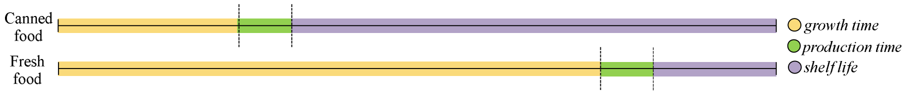
Table 1: Age & Size of Animals Ready for Slaughtering & Catching

Beef	Pork	Chicken	Fish
<10 months (veal)	≈ 5-6 months		>40-60* cm (salmon)
10-24 months (young cattle)	(90-105	≈ 40 days	>25-27* cm (flounder)
>24 months (cow-beef)	kilos)		>30-35* cm (cod)

**depends on catching area (e.g. North Sea, Baltic Sea, Kattegat) and sea (salt- or freshwater)*

Combined with the shelf life, fresh meat products' total lead-time differs largely from other food products. The total lead-time (growth, production and shelf life) of meat products, compared against a different food product, canned food, is illustrated in Figure 1. Canned food has relatively short growth time and long shelf life and may thus be handled (more or less strictly) in terms of inventory level and capital costs, due to the derived suitability for make-to-stock planning. Oppositely, fresh food has short shelf life with large growth time (animals' lifetime) and cannot be stored for more than few days (i.e. no stock building), meaning it must be handled in terms of risk of waste from poor planning, making it suitable for make-to-order planning.

Figure 1: Complete Lifetime of Different Product Groups



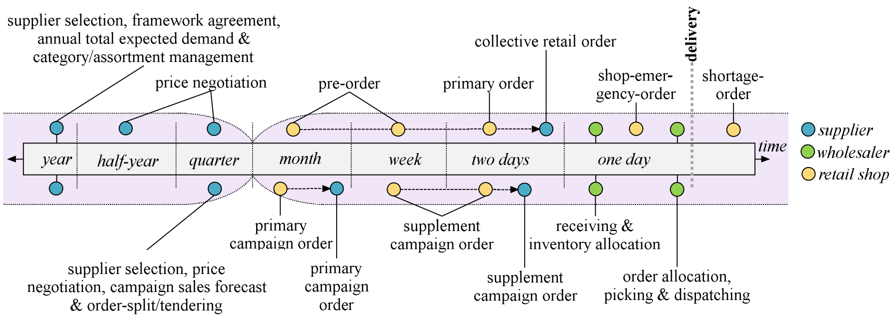
3. Methodology

This paper follows the explorative and empirical case study research approach of Flynn's six-stage design framework [16]. After investigating the current level of collaboration and differentiation in demand and supply chain planning, the purpose is to propose a differentiated planning approach that includes the raw materials' growth time. The ultimate goal of the approach is to meet consumers' requirements for availability. Since the product type and context is of particular importance in this case, studying in-depth in natural context enhances the insight and understanding of experiences [17, 18]. Four different meat types from 16 different suppliers, supplied by one of the largest wholesalers in Demark, are in focus in order to provide a generalizable view of differentiation in demand planning. Due to reasons of commercial confidentiality, the company' identity will not be revealed and called ABC throughout this article. This study uses information obtained through semi-structured interview with product manager and purchaser evolving from standardized questions about demand planning. The study focuses on products with less than 14 days shelf life for beef (veal/young cattle/cow), pork, chicken and fish.

4. Case Study

ABC (part of Scandinavia's biggest company within grocery and service trading) uses a centralized warehouse to supply the Danish market (almost 300 shops). ABC's overall goal is to be "the most value-driven company in Scandinavia", and they measure performance mainly through service level. In 2016, ABC sourced 53 beef products from five suppliers, 45 chicken products from two suppliers, 70 pork products from seven suppliers and 33 fish products from two suppliers, with down to 36 hours from order dispatch at shop to delivery. ABC uses a so-called "transit"-flow where products are ordered six days per week, in exact amounts, with no stock keeping. Depending on whether the shops order normal (i.e. assortment) or campaign products, ABC receives shops' orders at latest 18:00 two days or four weeks before delivery, respectively. ABC aggregates and sums up all incoming orders, and forwards these to respective suppliers. Shops are allowed to add additional supplementing orders or change existing orders down to two days before delivery. At the end of the year, ABC shares information with suppliers about total expected sales for upcoming year (including expected growth and expanding) as well as category/assortment changes. For campaigns, forecasted demand is sent to suppliers around three months before campaign start through a tendering-like process. If several suppliers are chosen to deliver the products, ABC splits the demand according to available capacity at supplier's site, price, quality level and delivery degree. No further demand information is shared, and the suppliers use historical incoming orders from ABC in their internal demand planning. Figure 2 shows ABC' planning cycles and information sharing, with activities for normal sale shown above the timeline and for campaign sale, below the timeline.

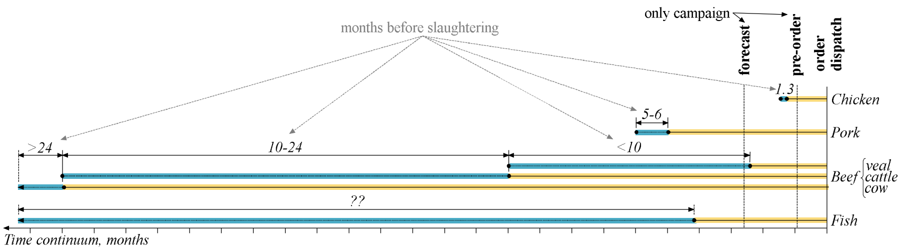
Figure 2: Time Continuum for Planning Activities



5. Analysis

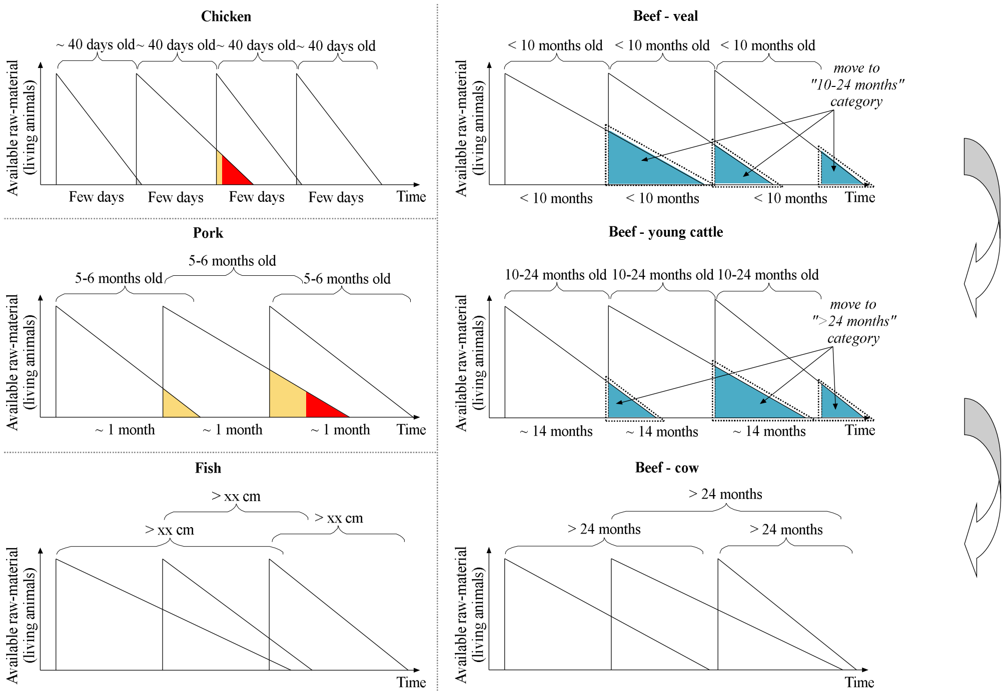
At overall level, ABC shares expected total annual demand (i.e. campaign and normal) for the upcoming year in November/early December. At lower level, the sharing differs, depending on whether it is campaign or normal demand. Campaign demand forecast and real orders are shared respectively three months and four weeks in advance for all products, allowing suppliers time to source raw materials needed (due to the larger demand). For normal demand, ABC expects suppliers to meet demand with two days' notice and does not share any information. The different meat types' lifetime characteristics influence the supply chain performance. Figure 3 shows timelines for each meat type with months back in time from the order dispatch, indicating the different times of information sharing between ABC and suppliers – relative to animals' life time and when they are given birth. The yellow area indicates the time it takes to raise animals until slaughtering back in time, while the blue area represents the time-window available for giving birth to the animals in order to have the animals ready for slaughtering and order dispatch.

Figure 3: Time Continuum for Planning of Meat Products versus Lifetime of Animals, in Months



Cleary there is inconsistency between ABC' uniform approach in information sharing with the suppliers and the time it takes to raise animals. For chickens campaign forecast is shared almost two months before they are born, which increases the noise in the supply chain due to premature information sharing and increases the forecasts errors due to untimely sharing of forecast. Instead, demand information should be shared at the time where the chickens need to be born, i.e. 40 days before order dispatch, meaning down to 42.5 days before order arrival in shops (when including the 36 hours from order dispatch in shop until arrival of order). This principle of lifetime dependent timely sharing of forecast also applies for other fresh meat types. For pork, beef and fish, the current approach means that forecast is shared months/years after animals are born creating a latent scarcity in availability of raw materials, deriving increased risk of not being able to source raw materials. This also means that upstream stages initiate production of animals according to isolated forecast, not driven by demand, meaning guess based forecasting with increased errors. In particular, fish are caught (and slaughtered) according to size and are heavily influenced by nature and climate, requiring forecasting longer time in advance to avoid unavailability. Hence, all meat types, but chicken, require relatively high level of collaboration and information sharing, i.e. timely demand planning. Figure 4 shows the animals available as raw material upstream in the supply chain (farmer stage) in relation to their lifetime planning window for slaughtering (after which they become unfit for use).

Figure 4: Time continuum for Planning of Animals and Their Lifetime Window



In Figure 4, Y-axis is available amount of raw materials for production (i.e. living animals) at a given time, and x-axis indicating the time. The yellow areas are amounts available within time-slack during which the animal's lifetime is acceptable for production, red areas are amounts available when lifetime exceeds upper limit (i.e. animals are too old for production) and blue areas are amounts when animals are too old, but suitable for different type of product. From the figure, chicken and pork face the chance of being too old and not fit for production (creating waste) with few days or one-month time-slack, respectively, which enhances the need for accuracy in demand planning. Fish only corresponds to a minimum size when caught and "the-bigger-the-merrier"-principle applies (i.e. bigger fish means more products per fish thus greater revenue). Opposite to all meat types, beef animals face a stepwise requirement: if animals are too old for one category (i.e. veal/cattle) they can be used for different product type (i.e. cattle/cow), and when reaching "cow"-step "the-bigger-the-merrier"-principle applies.

6. Discussion & Conclusion

One of the main findings is that sharing demand information relatively to the time it takes to raise the animals ready for slaughtering/catching (i.e. animals' lifetime) can allow upstream supply chain to be better prepared for the demand behavior. In turn, this may not only reduce forecast errors from untimely forecast sharing, which influences the service levels from supplier to ABC to the shops positively and derives higher revenue, it also reduce undesirable noise in the supply chain from premature demand information. Thus, sharing information timely align the upstream production and birth of animals to the real demand behavior. As a consolidator in the supply chain, the wholesaler must be able to interpret and plan to expected level of demand [2], “to be more proactive to anticipated demand and more reactive to unanticipated demand” [12]. From the theoretical framework, the longer time horizon to forecast the greater level of forecast error, meaning that forecasting and demand information sharing should be as timely as possible. By taking into consideration the total time of the product, in particular the animals’ lifetime and production time, it is possible to derive the timely point in time, at which forecast should be shared and point in time actual order should be dispatched. That is, just prior to the animals’ birth.

In order to ensure the overall efficient and effective demand and supply chain planning and thus encompass the different planning-steps at each supply chain stage (production planning, master production schedule, material requirements planning, capacity planning etc.) – and the time-horizon-related forecast errors, information should be shared with certain time-intervals throughout time, relative to the animals’ lifetime. Figure 5 illustrates demand forecasts’ error-distributions and their adjustment of mean and median values relatively to the forecasts’ time-horizon (the short time-horizon, the smaller error), hence also the risk of over- and undersupply of resources. The red area presents the chance of undersupply and stock out is greater than 100% service level (i.e. forecast X-n, X-2 and X). Green area shows the chance of oversupply and full delivery is greatest (i.e. forecast X-3 and X-1). Thus, depending on the individual animal’ lifetime (i.e. meat-type), demand forecast(s) should be shared differently through time – i.e. either several (for beef), few times (for pork) or a single time (for chicken). Hence, sharing demand information relatively to animals’ lifetime also means later information sharing for chicken products.

Figure 5: Forecasting Error Distribution through Time

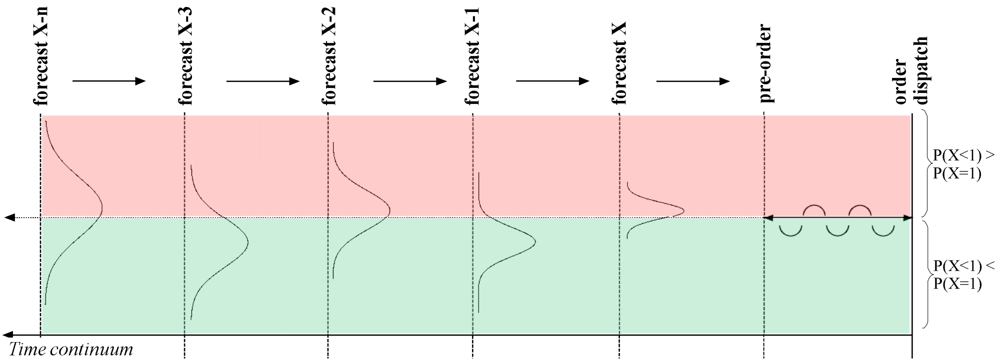
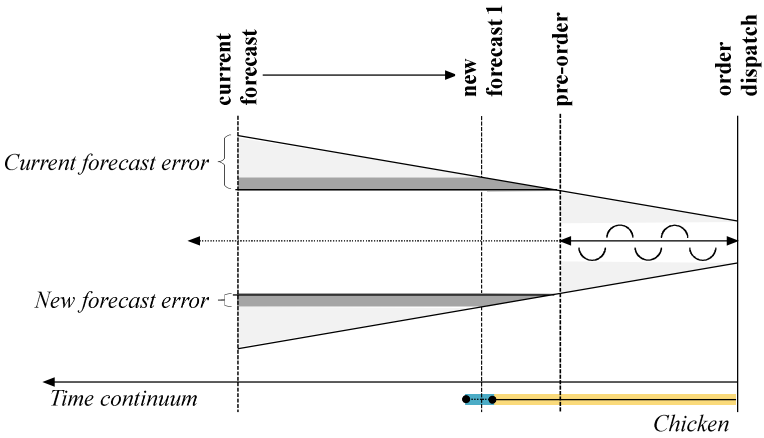


Figure 6: Reduction in Forecasting Error for Chicken Products



In Figure 6, ABC' current versus suggested point of forecast is shown. Since chickens require 40 days before ready for slaughtering, the postponement of demand sharing (from three months to around 40 days) will reduce errors in estimation and noise in the supply chain. Moreover, this will also reduce the chance of oversupply, and hence the chance of having chickens too old causing waste. For the other meat products, the differentiation is similarly influenced by animals' lifetime. Pork meat requires five to six months to become ready for slaughtering and demand forecast should be shared from around six months before order dispatch and on regular interval up until pre-order. Beef meat type is a stepwise product (veal/cattle/cow) and less sensitive to overestimation. If having too many raw materials (i.e. animals), they can be moved into different category – and when reaching "cow"-category, they follow "the-more-the-merrier"-principle. Fish type follows the "the-more-the-merrier"-principle, and is per se only sensitive to under-estimation since overestimation means greater value (keeping fish alive means bigger fish, hence more products from a single fish), in turn reducing the sensitivity in demand planning. Alike pork, demand information about beef and fish should similarly be shared on regular interval prior to order dispatch. From theoretical framework, the interval depends on different factors outside the scope of this paper, hereunder demand fluctuations and demand type.

This research has focused on differentiation for four major products groups in a single case study, and additional research is needed in terms of more product groups, more case companies and testing of suggested approach, to increase level of validity. Other meat-types are seasonal and/or only sold for limited time during a year, which may have influence (products in this study have constant demand throughout year). Also, research should be made in reduction of relative waste amount from having too large amount of products in shops, in regards to differentiated pricing of products when getting closer to expiration date [19] and its influence on demand behavior.

References

1. Mena, C., Terry, L.A., Williams, A., Ellram, L.: Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector. Int. J. Prod. Econ. 152, 144–158 (2014).
2. Kuhn, H., Sternbeck, M.G.: Integrative retail logistics: An exploratory study. Oper. Manag. Res. 6, 2–18 (2013).
3. Kaipia, R.: Coordinating Material and Information Flows with Supply Chain Planning. Int. J. Logist. Manag. 20, 144–162 (2009).
4. Romsdal, A.: Differentiated Production Planning and Control in Food Supply Chains. (2014).
5. Entrup, M.L.: Advanced Planning in Fresh Food Industries, Integrating Shelf Life into Production Planning. Physica-Verlag Heidelberg, Berlin (2005).
6. Ivert, L.K., Dukovska-Popovska, I., Kaipia, R., Fredriksson, A., Dreyer, H.C., Johansson, M.I., Chabada, L., Damgaard, C.M., Tuomikangas, N.: Sales and Operations Planning: Responding to the Needs of Industrial Food Producers. Prod. Plan. Control. 26, 280–295 (2015).
7. Kampen, T.J. Van, Akkerman, R., Donk, D.P. Van: SKU Classification: a Literature Review and Conceptual Framework. Int. J. Oper. Prod. Manag. 32, 850–876 (2012).
8. Hanke, J.E., Wichern, D.W.: Business Forecasting. Pearson Prentice Hall, New Jersey (2009).
9. Williams, T.M.: Stock Control with Sporadic and Slow-Moving Demand. J. Oper. Res. Soc. 35, 939–948 (1984).
10. Boylan, J., Syntetos, A., Karakostas, G.: Classification for Forecasting and Stock Control: A Case Study. J. Oper. Res. Soc. 59, 473–481 (2008).
11. Hübner, A.H., Kuhn, H., Sternbeck, M.G.: Demand and Supply Chain Planning in Grocery Retail: an Operations Planning Framework. Int. J. Retail Distrib. Manag. 41, 512–530 (2013).
12. Lambert, D.M.: Supply Chain Management - Processes, Partnership, Performance. Supply Chain Management Institute, Sarasota (2008).
13. Chen, F., Drezner, Z., Ryan, J.K., Simchi-levi, D., Chen, F., Drezner, Z., Ryan, J.K.: Quantifying the Bullwhip Effect in a Simple Supply Chain: The Impact of Forecasting, Lead Times, and Information. Manage. Sci. 46, 436–443 (2000).
14. Adebanjo, D.: Understanding Demand Management Challenges in Intermediary Food Trading: A Case Study. Supply Chain Manag. An Int. J. 14, 224–233 (2009).
15. Fisher, M., Raman, A.: Flexible Supply Chains. In: The New Science of Retailing. pp. 105–131. Harvard Business Press, Boston (2010).
16. Flynn, B.: Empirical Research Methods in Operations Management. J. Oper. Manag. 9, 250–284 (1990).
17. Yin, R.K.: Case Study Research: Design and Methods. SAGE Publications Inc, California (2014).

18. Eisenhardt, K.M.: Building Theories from Case Study Research. Acad. Manag. Rev. 14, 532–550 (1989).
19. Hvolby, H.H., Steger-Jensen, K.: Managing Cannibalization of Perishable Food Products in the Retail Sector. Procedia Comput. Sci. 64, 1051–1056 (2015).

PAPER #2

Information Sharing for Replenishment Planning and Control in Fresh Food Supply Chains: A Planning Environment Perspective

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Information Sharing for Replenishment Planning and Control in Fresh Food Supply Chains: A Planning Environment Perspective

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Abstract. This study explores how planning environment characteristics (PECs) of a fresh food processor affect the information sharing during replenishment planning and control (RP&C) in fresh food products (FFP) supply chains. The research design is a multiple case study covering a triadic SC comprising five FFP processors, one wholesaler and nine retail stores. The analysis investigates when and where the product-, demand-, supply- and production-related PECs impact the mate-rial requirements planning and master production scheduling at the FFP processors and how these affect the information sharing at a product level. Findings show how the information sharing should be differentiated at a product level, rather than the dominating demand type or processor level differentiation. Based on abductive reasoning the study generates propositions for appropriate frequency, timing, direction, modality, content and dynamism of information sharing during RP&C.

Keywords: information sharing, planning and control, supply chain, perishable, retail

1. Introduction

Fresh food products (FFPs) contribute significantly to retail grocery sales (Nielsen 2018), but the FFP supply chains (FFPSC) struggle to meet the consumer requirements for availability and freshness (Hübner, Kuhn, and Sternbeck 2013; BlueYonder 2017). The FFP shelf life is down to few days from processing to expiration (Man 2016), and inventories cause increased waste-levels (Eriksson, Strid, and Hansson 2014; Mena et al. 2014). Increasing the FFPs' remaining shelf life improves freshness and waste-levels (Broekmeulen and van Donselaar 2017) Automated replenishment planning and control (RP&C) between two FFPSC stages (e.g. wholesaler – retail stores) is one way to improve remaining shelf life while maintaining availability (Kiil et al. 2018). How-ever, it focuses on how the wholesaler internally decides when and how much to order on behalf of the retail stores. The majority of FFPs are processed, delivered to wholesaler and distributed to retail stores daily, and the FFPSC tiers link the RP&C through information sharing cycles (Chopra and Meindl 2010; Kembro and Näslund 2014). It is thus of interest to expand the internal decision-making and two-stage scope to encompass the information sharing during the supply chain-wide RP&C.

Information sharing plays a crucial role in the supply chain collaboration and RP&C is part of such a collaboration. Frequent and timely sharing of demand information (e.g. demand forecasts, customer orders and inventory levels) and supply information (e.g. raw material availability, sup-ply lead-times and available processing capacity) can contribute to reducing under-/oversupply of FFPs (Lusiantoro et al. 2018; Siddh, Soni, and Jain 2015) and improving product freshness (Ferguson and Ketzenberg 2006). However, information sharing in itself does not automatically improve performance (Baihaqi and Sohal 2013). To avoid losses from sharing too much or irrelevant information (Choi, Li, and Wei 2013), or too early or late (Xu, Dong, and Xia 2015), the ef-fective information sharing should be differentiated and reflect the FFP characteristics rather than being automated according to general inventory rules (e.g. order-up-to level) (Kiil et al. 2018) and the same across products and FFPSCs (Nakandala, Samaranayake, and Lau 2017).

Common RP&C practices entail demand information sharing with the same pre-agreed timing for all FFPs, e.g. “when the actual inventory levels and retailers’ orders are known” (Alftan et al. 2015, 244) or when inventory levels reach a certain point (Kiil et al. 2018). The timing varies at FFP processor level or by specific demand characteristics (VICS 2004; Alftan et al. 2015). But, it may be beneficial to differentiate the timing at a lower level (Huang, Lau, and Mak 2003).

In a context where there is no vendor managed set-up, demand information is normally shared by the wholesaler/retail stores and used as input in FFP processor’s planning of raw material sourcing (i.e. material requirements planning (MRP)) and scheduling of FFP processing (i.e. mas-ter production scheduling (MPS)). However, the MRP and MPS are influenced by different raw material availability during the year as well as a wide variety of end-products per raw material with specialized and complex processing requirements (i.e. different processing) (Romsdal 2014; Entrup 2005). Such different so-called planning environment characteristics (PECs) indicate that the MRP and MPS e.g. need different information at different timings and with different frequencies depending on the given FFP. Hence, that it might be more effective to share information based on the PECs rather than with fixed timing and content across all products. Thus, we propose that the effective demand and supply information sharing should reflect the PECs at the product level.

This study takes on a triadic supply chain focus with FFP processor, wholesaler and retail store(s), and investigates how information sharing during RP&C should be differentiated according to FFP processor's MRP and MPS. To identify the drivers of differentiation, this research investigates which PECs affect the MRP decision-making as to when and how much raw material to order, and, the MPS decision-making as to when and how many FFPs to process at the FFP processor. From this we explore which requirements the PECs set forth to the effective demand and supply information sharing when the wholesaler plans and controls replenishments. We address three research questions (RQs):

RQ1: What are the PECs of MRP and MPS at FFP processors?
RQ2: How do the PECs differ across different FFPs?
RQ3: How should demand and supply information sharing be differentiated according to PECs during RP&C?

The following section presents the theoretical background and methodology of the study. We conduct a multiple case study with five FFP processors, one wholesaler and nine franchise-based retail stores, for different beef, pork, chicken and fish products. Next, we ana-lyse the requirements for information sharing in the cases. We then abductively infer propositions for effective information sharing, and discuss these, ending with a conclusion and further research. This paper contributes to the existing literature by providing empirical and contextual insights on effective information sharing during RP&C in the triadic FFPSC, given the PECs impact on the FFP processors' MRP and MPS.

2. Theoretical Background

The RP&C governs "the operational planning and control of inventory replenishment in supply chains, where the focus is largely on information sharing (…) between supply chain actors" (Jonsson and Holmström 2016, 64). This study focuses specifically on the RP&C from a wholesaler point of view and the information sharing with FFP processors. Since the FFP processor transforms the raw materials into ready FFPs which cannot be stored per se according to "make-to-order" principle (for majority of FFPs), and wholesaler merely picks and packs FFPs for further distribution, the information sharing should be contingent on the FFP processors' MRP and MPS. The MRP, as it provides a detailed plan of when to order raw materials, and how much, to process and balance supply with wholesaler's demand, thereby satisfying retail stores' demand. The MPS, as it provides a detailed schedule of when to process the FFPs according to the overall sales and operations planning and incoming wholesaler orders. The literature has studied how PECs affect the MRP and MPS at a producer/processor stage (e.g. Jonsson and Mattsson 2003; Olhager and

Rudberg 2002). However, when taking a supply chain perspective, it is vital to understand the de-mand and supply information sharing during the RP&C, and how the value of information sharing for the MRP and MPS is affected by the PECs. Hence, the theoretical background starts by defining and presenting information sharing and its different facets, followed by identifying the PECs of importance to the information sharing of FFPSCs.

2.1. Information Sharing and Its Facets

Information sharing is the “inter-organizational sharing of data, information and/or knowledge in supply chains“ (Kembro and Näslund 2014, 181) with focus on “capturing and disseminating timely and relevant information for decision-makers to plan and control supply chain operations“ (Simatupang and Sridharan 2005a, 46). Further, information sharing tends to be a fundamental part of RP&C practices (Pramatari and Miliotis 2008; VICS 2004; Choi and Sethi 2010; Marquès et al. 2010; Alftan et al. 2015). The FFPs benefit more from a high level of information sharing than products with long shelf life (Lusiantoro et al. 2018).

The literature mentions several different facets of information sharing when characterizing and structuring the sharing of the right information with the right parties at the right time at the right frequency in the right way under the right circumstances. Table 1 summarises the literature and provides a taxonomy on information sharing, by identifying its facets, and, the research design in which they are discussed. Table 1 does not represent an exhaustive literature review but merely serves as the basis for identifying the information sharing facets to guide further analysis. The research design of each study is depicted as to if it is theoretical/empirical/simulation/review, supply chain stages included, supply chain structure, type of information flow and product con-text. The discussed facets are marked by “x”.

Table 1: Facets of information sharing in literature

Author	Research design					Information sharing facets										Total facets
	Focus of design	Stages included	Structure studied	Information flow	Context in focus	Frequency	Timing	Direction	Modality	Content	Dynamism	Incentive	Sourcing	Handling	Quality	
Alftan et al. (2015)	TE	PWR	T	S	G			x	x	x			x	x		5
Barratt and Oke (2007)	E	PWR	D	S	(G)R				x	x		x				3
Cai, Jun and Yang (2010)	E	S	I	U	A				x	x		x				3
Cao and Zhang (2011)	E	S	I	U	A	x				x					x	3
Carr and Kaynak (2007)	E	S	I	U	O			x	x	x		x				4
Chen, Wang and Yen (2014)	E	S	I	U	O		x	x		x						4
Christensen, Dukovska-Popovska, and Steger-Jensen (2017a)	T	PW	U	U	GFRP		x								x	2
Christensen, Mantravadi, et al. (2019b)	T	PWR	T	S	GFRP		x					x	x	x		4
Dimitriadis and Koh (2005)	E	P	I	U	A				x	x						2
Ding et al. (2014)	E	P	I	U	GFP	x		x	x	x					x	5
Dreyer et al. (2018)	E	WR	I	U	GFP				x	x		x				3
Fawcett et al. (2007)	E	PRA	I	U	A				x			x				2
Ha, Park, and Cho (2011)	TE	P	I	U	A	x			x			x				3
Huang, Lau and Mak (2003)	R	A	A	U	A	x	x	x	x	x		x	x			7
Hung et al. (2011)	E	P(R)	I	U	A				x	x					x	3
Ivert et al. (2015)	E	P	I	U	GFP	x			x	x			x			4
Jonsson and Mattsson (2013)	S	PRC	T	C	A	x			x	x	x	x				5
Jonsson and Myrelid (2016)	ER	PA	I	U	O	x		x	x	x					x	5

	Research design					*Information sharing facets*										
Author	**Focus of design**	**Stages included**	**Structure studied**	**Information flow**	**Context in focus**	**Frequency**	**Timing**	**Direction**	**Modality**	**Content**	**Dynamism**	**Incentive**	**Sourcing**	**Handling**	**Quality**	**Total facets**
Kaipia et al. (2017)	E	PR	D	S	G	x	x	x		x	x	x			x	7
Kehoe and Boughton (2001)	T	P	U	U	A		x		x	x						3
Klein and Rai (2009)	E	PWR	D	S	(R)A			x	x	x		x				4
Kembro, Selviaridis, and Näslund (2014)	R	A	A	A	A			x	x	x		x	x			5
Kembro and Näslund (2014)	R	A	A	A	A	x		x	x	x		x				5
Kembro and Selviaridis (2015)	E	PR	D	CD	G					x		x				2
Kiil et al. (2019)	E	PWR	D	S	GFRP	x	x	x	x	x					x	6
Lee and Ha (2018)	(T)E	P	I	U	A	x		x	x	x	x	x				5
Li, Ye, and Sheu (2014)	(T)E	P	I	U	A				x	x		x				3
Lusiantoro et al. (2018)	R	A	U	U	GFP	x	x		x	x		x			x	6
Moberg et al. (2002)	E	P	I	U	A				x	x		x			x	4
Mohr and Nevin (1990)	T	A	U	U	A	x		x	x	x						4
Montoya-Torress and Ortiz-Vargas (2014)	R	A	A	U	A					x		x				2
Myrelid and Jonsson (2019)	E	PA	D	CD	O	x		x	x	x					x	5
Nakandala, Samaranayake, and Lau (2017)	R	PWRC	E	S/U	GFP	x	x	x	x	x						5
Paulraj, Lado and Chen (2008)	E	A	I	S	A	x	x		x	x	x	x			x	7
Pålsson and Johansson (2009)	E	P	I	U	(F)O	x		x								2
Shey, Yen, and Chae (2006)	E	PR	D	S	O	x		x	x	x		x				5
Simatupang and Sridharan (2005a)	(T)E	PR	D	U	A		x	x		x			x	x	x	6
Simatupang and Sridharan (2005b)	T	PA	U	U	A		x	x		x			x	x	x	6
Tan et al. (2010)	TE	P	I	U	A			x	x			x				3
Vanpoucke, Boyer, and Vereecke (2009)	E	P(B)	D	S	(G)PO		x	x	x	x		x			x	6

	Research design					Information sharing facets										
Author	**Focus of design**	**Stages included**	**Structure studied**	**Information flow**	**Context in focus**	**Frequency**	**Timing**	**Direction**	**Modality**	**Content**	**Dynamism**	**Incentive**	**Sourcing**	**Handling**	**Quality**	**Total facets**
Watabaji et al. (2016)	E	PW	D	U	A	x			x	x					x	4
Xu, Dong, and Xia (2015)	T	PR	D	S	A		x			x						2
Yigitbasioglu (2010)	E	PWR	I	U	A	x		x		x	x	x			x	6
Yu et al. (2013)	E	P	I	U	A			x	x	x						3
Zhou and Benton (2007)	E	P	I	U	A				x	x	x				x	4
Total facets						18	12	22	31	37	6	23	7	4	16	176

Note: Focus of design: *E = empirical (incl. case study and surveys), T = theoretical, S = simulation, R = review.*
Stages included: P *= processor, W = wholesaler (incl. traders), R = retail store, C = customer, A = anonymous buying/supplying party.*
Structure studied: *I = individual (i.e. one stage), D = dyadic, T = triadic, E = extended, A = all, U = undefined/generic.*
Information flow: *S = serial, C = convergent, D = divergent, U = undefined/generic.*
Context; *G = grocery, F = food, P = perishable, R = retailing, O = other, A = anonymous/general.*
For all: () = partly in focus.

Ten facets of information sharing have been identified based on literature: frequency, timing, direction, modality, content, incentive, sourcing, handling, dynamism and quality. The facets incentive, sourcing and handling, are omitted from the further study as they do not change according to the individual product but rather product-/supplier-group or inter-organisational structure (Kembro, Selviaridis, and Näslund 2014; Simatupang and Sridharan 2005b; Simatupang and Sridharan 2005a; Kembro and Näslund 2014). As an example, sourcing governs from where the information is collected/obtained which e.g. for POS-data, orders, master data is the same place regardless of products (e.g. retail stores' cashier system or ERP systems). Quality has several sub-facets: complete, concise, reliable, timely, valid, accessible, formatting appropriate amount, credible, relevant and understandable (Gustavsson and Wänström 2009; Moberg et al. 2002; Myrelid and Jonsson 2019). Information quality impacts the level of information sharing between supply chain parties (Moberg et al. 2002) and is particularly relevant for perishables (Lusiantoro et al. 2018). Yet, given the number of sub-facets and scope of this study, we exclude quality as a facet in its entirety and include only timing and frequency given their relevance to sharing information. Hence, frequency, timing, direction, modality, content and dynamism may change depending on the individual product' PECs. These are elaborated in the following.

Frequency. The frequency (and possibly duration) of contact between organizational members (Mohr and Nevin 1990; Watabaji et al. 2016) may increase/decrease, depending on the individual product (i.e. shelf life and degradation) (Lusiantoro et al. 2018), the related task/decision, and level of collaboration (Cao and Zhang 2011; Pålsson and Johansson 2009). It may either be un-scheduled and conducted when needs arise or scheduled to a specified time ranging from real-time and up to annually (Kembro and Näslund 2014; Ding et al. 2014; Ha, Park, and Cho 2011).

Timing. The earliness refers to how far in advance of an action/decision-making should the in-formation be shared (Huang, Lau, and Mak 2003; Kiil et al. 2019; Gustavsson and Wänström 2009). Different PECs, such as animal lifetime (Christensen, Dukovska-Popovska, and Steger-Jensen 2017) and processing setup (Romsdal 2014; Entrup 2005), impact the timing of sharing (Simatupang and Sridharan 2005a). Not sharing the information timely affects planning and con-trol (Kehoe and Boughton 2001) through reduced performance (Xu, Dong, and Xia 2015; Vanpoucke, Boyer, and Vereecke 2009), increased inventories and reduced ability to respond to demand fluctuations (Chen, Wang, and Yen 2014; Huang, Lau, and Mak 2003). When sharing in-formation close to the decision-making, the information "freshness" (hence validity) improves due to, e.g. reduced uncertainty and noise (Xu, Dong, and Xia 2015; Chen, Wang, and Yen 2014). This is vital for FFP freshness (Nakandala, Samaranayake, and Lau 2017; Lusiantoro et al. 2018).

Direction. For inter-firm context, the horizontal movement of information may be either up-stream or downstream across dyadic, triadic or extended supply chains, while the vertical movement may be between same-stage parties. The direction of information may depend on, e.g. the demand forecasting capabilities (Alftan et al. 2015) or supply chain role (Hübner, Kuhn, and Sternbeck 2013). While in close collaborations the direction is two-ways (up- and downstream), it is usually only upstream in less collaborative constellations.

Modality. Modality concerns the method and medium of sharing the information, generally either formal or informal (Mohr and Nevin 1990; Kembro, Selviaridis, and Näslund 2014; Watabaji et al. 2016). Formal modality is regularized and structured, while informal is spontaneous and nonregularized (Mohr and Nevin 1990). The mediums of sharing information include, e.g. face-to-face, phone, fax, e-mail, EDI, web-enabled portals, internet, ERP system and data warehouse management (Kembro, Selviaridis, and Näslund 2014; Watabaji et al. 2016).

Content. The specific information content to share relates to the demand and supply (Mohr and Nevin 1990; Kembro, Selviaridis, and Näslund 2014). Various content may vary in relevance (Simatupang and Sridharan 2005b). For FFPSC, additional information about, e.g. temperature, waste amounts, remaining shelf life may also be shared (Lusiantoro et al. 2018; Ferguson and Ketzenberg 2006). The information may not be the same for all partners, but be standardized or customized (Kembro and Näslund 2014). The content depends on the context (Kembro, Selviaridis, and Näslund 2014) and decision making (Huang, Lau, and Mak 2003), and may vary in volume, type and aggregation (i.e. the level of detail) (Watabaji et al. 2016). In this study, content relates to the demand and supply quantities used as information input to wholesaler's RP&C and FFP processor's MRP and MPS. Thus, demand information content includes inventory levels, campaign/normal demand forecast, campaign/normal (purchase) order and POS data – for all FFPSC stages. Supply information includes supply disruptions, MPS processing schedules, ca-pacity and raw material availability at FFP processor (Jonsson and Mattsson 2013; Montoya-Torres and Ortiz-Vargas 2014; Kiil et al. 2019; Alftan et al. 2015).

Dynamism. The changing needs for information may or may not be predictable. The literature considers dynamism as the pace of unpredictable changes in the supply chain, e.g. raw material availability. The greater the dynamism, the higher the value of information sharing (Kaipia et al. 2017; Alftan et al. 2015). "Effective information sharing mediates the impact of supply chain dynamism on supply chain practices" (Zhou and Benton 2007, 1360). Vis a vis, we use dynamism as a facet in that the need (i.e. content) and intensity (i.e. frequency) of information sharing may change through time depending on environmental uncertainty (Yigitbasioglu 2010), which may in turn affect e.g. modality and timing.

In our general literature review, studies predominantly focus on information sharing in individual (i.e. single stage) (21) or dyadic (11) relationships with only four out of 45 studies including three or more supply chain stages. The product/industry context is predominantly unspecified (25) with only eight studies specifically including grocery, perishable and FFP context. During the past four-five years, there has been an increase in studies focusing on grocery/perishable/food context as well as a general towards context-specific research. The articles cover information sharing in terms of sales and operations planning at processor' level (Ivert et al. 2015; Dreyer et al. 2018), forecasting quality in relation to animal lifetime aggregated at animal type level (Christensen, Dukovska-Popovska, and Steger-Jensen 2017), generic fresh food context (Nakandala, Samaranayake, and Lau 2017; Lusiantoro et al. 2018), information utilization during planning (Kiil et al. 2019), and impact of information quality on product quality (Ding et al. 2014). Almost all studies include content and modality, while dynamism, sourcing and handling are less included. Seventeen studies include five facets or more and they tend to be empirical studies or reviews, while analytical and theoretical studies tend to cover less facets. Although e.g. Alftan et al. (2015) considers certain information sharing facets as part of RP&C, no single study considers the facets at individual product-level in the context of FFP replenishment in a triadic FFSCP with contingency on FFP processors MPS and MRP.

2.2. Planning Environment Characteristics (PECs)

The FFPs are particularly challenging for the RP&C due to: perishability (Ferguson and Ketzenberg 2006; Ferguson and Koenigsberg 2007), demand and supply seasonality, weather con-ditions, frequent promotional activities and product introductions (Taylor and Fearne 2009; van Donselaar et al. 2010; Alftan et al. 2015; Hübner, Kuhn, and Sternbeck 2013; Fredriksson and Liljestrand 2015), long (uncertain) growth periods with inadequate quality and/or yield-ing/harvesting of products (Christensen, Dukovska-Popovska, and Steger-Jensen 2017; Ferguson and Koenigsberg 2007), specialized production/ processing processes (Romsdal 2014). These characteristics represent PECs which put special requirements on the information sharing since they affect the MRP and MPS at the FFP processor (Entrup 2005; Romsdal 2014; Hübner, Kuhn, and Sternbeck 2013; Ivert et al. 2015).

Table 2 describes PECs identified in literature and considered relevant for differentiating in-formation sharing in FFPSCs. The PECs are discussed in a variety of planning and control con-texts, such as: manufacturing/processing planning and control (Olhager and Rudberg 2002; Romsdal, Strandhagen, and Dreyer 2014), sales and operations planning (Ivert et al. 2015; Dreyer et al. 2018), detailed material planning, capacity planning, scheduling and sequencing (Jonsson and Mattsson 2003), supply chain planning and exceptions management (Alftan et al. 2015). Certain PECs, such as independent versus dependent demand, type of retail chain (e.g. online, super-market, discount etc.), inventory management (i.e. ability to keep stock) and customer base complexity, have been omitted in this study. This, since the focus is on FFPs with independent demand and limited ability for storing, if any, in the same retail chain (i.e. same customer base). The different characteristics can be categorized as: demand-, supply-, production- and product-related.

Table 2: Overview of relevant PECs in literature

PEC	Type	Description
Volume	Demand	number of products produced per year (Jonsson and Mattsson, 2003; Romsdal et al., 2014; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Type of procurement ordering	Demand	order by order procurement or blanket order release from a delivery agreement (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Demand type	Demand	demand from forecast, calculated requirements or from customer order allocations (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Time distributed demand	Demand	whether the demand is distributed over time or an annual figure (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Source of demand	Demand	whether demand is stock replenishment order or customer order (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Inventory accuracy	Demand	the extent to which there is accuracy in stock on hand data (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Demand-stimulating events	Demand	whether demand is stimulated by promotions, seasonality, product interrelation (Dreyer et al., 2018)
Availability requirements	Demand	whether products are expected to have constant availability or not (Dreyer et al., 2018; Ivert et al., 2015)
Demand frequency/lumpiness	Demand	number of times per year products are ordered (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Customer service elements	Demand	inventory service levels, lead times, and delivery precision, quality and flexibility (Romsdal et al., 2014; Wänström and Jonsson, 2006)
Ramp-up level	Demand	the smoothness of the phase-in/out: gradually increased/decreased demand or a phase-in/out on a specific date (Wänström and Jonsson, 2006)
Demand uncertainty	Demand	the uncertainty of demand, measured as forecast accuracy or the coefficient of variation (CoV) (Ivert et al., 2015; Romsdal et al., 2014; Wänström and Jonsson, 2006)
Seasonality of supply	Supply	the extent to which there is seasonality in supply (Dreyer et al., 2018)
Supplier base complexity	Supply	number of suppliers per year, their geographical localisation, and supplier segments (Bozarth et al., 2009; Ivert et al., 2015) for the different products (Dreyer et al., 2018)
Multiple brands	Supply	number of different brands for the same type of product; (Dreyer et al., 2018)

PEC	Type	Description
Capacity constraints	Supply	the capacity constraints at processor (Dreyer et al., 2018)
Supplier service elements	Supply	inventory service levels, lead times, and delivery precision, quality, flexibility, etc. (Wänström and Jonsson, 2006)
Material supply scrap level	Supply	the percentage of materials supply chain batch that is scrapped (Wänström and Jonsson, 2006)
Type of procurement ordering	Supply	whether the order is by order procurement or blanket order releases from a delivery contract (Wänström and Jonsson, 2006)
Lot size	Supply	the typical lot size purchased (Wänström and Jonsson, 2006)
Long and/or unreliable supplier lead times	Supply	the degree to which supplier lead times are long and/or unreliable (Bozarth et al., 2009)
Number of suppliers	Supply	the number of suppliers to the given company/product (Bozarth et al., 2009)
Supply uncertainty	Supply	the predictability and variability in supply (Ivert et al., 2015)
BOM complexity	Product	the number of levels in the bill of material and the typical number of items on each (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Product complexity and variety	Product	the complexity of the product and existence of optional product variants (Dreyer et al., 2018; Ivert et al., 2015; Jonsson and Mattsson, 2003; Romsdal et al., 2014; Spenhoff et al., 2014)
Degree of value added at order entry	Product	the extent to which the manufacturing of the products is finished prior to receipt of customer order (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Proportion of customer specific items	Product	the extent to which customer specific items are added to the delivered product, e.g. the addition of accessories (Jonsson and Mattsson, 2003; Spenhoff et al., 2014) (Wänström and Jonsson, 2006)
Product/item value	Product	the value of the item or product (Wänström and Jonsson, 2006)
Perishability and shelf life	Product	whether products have finite or fixed lifetime (Dreyer et al., 2018; Ivert et al., 2015; Romsdal et al., 2014)
Product life cycle (PLC)	Product	the product’ stage in the life cycle (new/introduction, growth, maturiy, decline) (Romsdal et al., 2014)
Inter-relationships in demand among products	Product	the extent to which there is inter-relationships in demand among products (Dreyer et al., 2018)

PEC	Type	Description
Shortening product life cycles	Product	whether there are shortening product life cycles, more frequent new product introductions; (Dreyer et al., 2018)
Heterogeneity	Product	the extent to which there is heterogeneity between the products (Dreyer et al., 2018)
Number of SKUs	Product	the range of a company's product offering (Dreyer et al., 2018; Ivert et al., 2015)
The rate of change in the product portfolio	Product	the number of product launches and removals per year (Ivert et al., 2015)
Batch size	Production	the typical manufacturing order quantity (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Through-put time	Production	the typical manufacturing through-put times of the products (Ivert et al., 2015; Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006)
Number of operations	Production	the number of operations in typical routings (Jonsson and Mattsson, 2003; Spenhoff et al., 2014)
Production lead time	Production	the product's production lead time; (Romsdal et al., 2014)
Volume flexibility	Production	the ability to handle the variability in demand volumes (Wänström and Jonsson, 2006)
Product mix flexibility	Production	the ability to handle the variability in demand between products in marketed product lines (Wänström and Jonsson, 2006)
Delivery flexibility	Production	the ability to handle the variability in open customer orders (Wänström and Jonsson, 2006)
Production network complexity	Production	the level of production network complexity; (Ivert et al., 2015)
Manufacturing strategy	Production	the type of manufacturing strategy (Ivert et al., 2015)
Production uncertainty	Production	the extent to which there is production uncertainty (Ivert et al., 2015; Romsdal et al., 2014)
Phase-in/out date	Production	whether there is a fixed date or a date that can be adjusted manually (Wänström and Jonsson, 2006)
MP method	Production	whether the planning is MRP, kanban, re-order point, fixed order interval, etc. (Wänström and Jonsson, 2006)
Planning frequency	Production	whether the planning is transaction based, daily or weekly planning (Wänström and Jonsson, 2006)
Planning periods	Production	whether the planning periods are bucketless, daily or weekly time buckets (Wänström and Jonsson, 2006)
Time fences	Production	specifies the periods in which various types of change can be dealt with (Wänström and Jonsson, 2006)

3. Research Methodology

An exploratory multiple case-study (Flynn et al. 1990) is selected to analyse demand and supply information sharing in the FFPSC during RP&C, and how it is affected by the PECs impacting processor's MRP and MPS. This provides empirical insight and evidence for theoretical elaborations (Yin 2014; Barratt, Choi, and Li 2011) as well as an in-depth understanding of experiences and processes in a real-world context (Eisenhardt 1989; Meredith 1998). Using several FFP processors and retail stores reduces the risks of misunderstanding and false generalization from single events, and increases the external validity through more robust and testable theory (Barratt, Choi, and Li 2011; Eisenhardt 1989). Propositions are inferred through abduction i.e. best explanation to observed phenomenon (Kovács and Spens 2005). To guide the study, a semi-structured literature review on information sharing facets (i.e. Table 1) was carried out by searching for in-formation sharing/flow/transfer/exchange and facets/dimension, using different ways of spelling, in four major databases (ProQuest, Emerald Insight, Elsevier and ABI/INFORM). The references in the sample articles were used to identify other papers on information sharing (facets) i.e. snow-balling.

3.1. Case Selection

The study includes one wholesaler (Wholesaler), five FFP processors of meat and seafood (Beef1, Beef2, Pork, Chicken and Fish) and nine retail stores (Retail1 to 9). The wholesaler was selected based on relevance, existing collaboration and ongoing research protocols. The processors with the largest demand of meat and seafood FFPs from wholesaler were selected based on one year's data. Initially seven processors were selected, but later reduced to five due to lack of access. The ten retail stores with the largest and most varying demand to the wholesaler (out of the retail chain's 329 stores) were selected based on one year's data. The selection of retail stores was evaluated by the retail chain (franchisor) to ensure the greatest potential of providing knowledge and information cf. franchising setup. Three stores were changed due to inability to participate and low knowledge on the subject matter. Two stores with great knowledge about close-to-expiration sales were added. Barriers related to willingness in sharing information (Fawcett et al. 2007; Montoya-Torres and Ortiz-Vargas 2014) were not present in the study.

3.2. Case Description

Table 3 provides a summary of each case. While Beef1 only delivers to national customers, the other processors also deliver to customers worldwide. All processors (except Fish and, for some FFPs, Beef1) process domestic raw material with a few hours transport before slaughtering, and deliver to the wholesaler from domestic facilities. The wholesaler is one of the largest grocery wholesalers in Denmark, supplying products to hundreds of different discount and convenience stores. Retail1-9 belong to the fastest growing franchise-based discount chain in Denmark. Both Wholesaler and Retail1-9 are owned by one of

Scandinavia's largest players in the grocery market. As opposed to capital chains, in franchise-based retail chains each store is owned and man-aged by the individual franchisee, although chain-wide campaigns are still managed centrally. Thus, while capital chains typically entail centralized RP&C, franchise-based chains incorporate decentralized RP&C, where each store makes decision about local campaigns, when and how much to order.

Table 3: Case features of FFP processors, wholesaler and retail stores

Case study	Market scope	Type of customer	Supplier base	# FFP SKUs delivered	# boxes sold in one year (2017 to 2018)	Product types in assortment
Beef 1	national	retail chains, stores, butchers, wholesaler	national farmers and slaughter-houses	14	247,000	cattle, veal, beef, mix FFPs
Beef 2	national, global export	retail chains, stores, restaurants, butchers, food service, wholesaler, meat processors, export	national farmers (unitholders)	75	2,152,000	cattle, veal, beef, organic beef, supreme, mix FFPs
Pork	national, European export	retail chains, stores, hotels, restaurant, butchers, food service, wholesaler, meat processors, export	national farmers and slaughter-houses	47	867,000	pork, organic pork, mix FFPs
Poultry	national, Nordic export	retail chains, stores, restaurants, food service, wholesalers and export	national farmers	26	325,000	poultry, organic poultry, mix FFPs
Fish	national, European export	retail chains, fish stores and wholesalers	auctions and farmers	42	757,000	seafood, mix FFPs, ready-to-eat FFPs
Whole-saler	national	retail chains, convenience chains, stores, export	national FFP processors	303	89,646,000	cattle, veal, beef, supreme, organic beef,

Retail 1-9	Zealand, Jutland	consumers	Wholesaler	269-289	206,000-535,000	pork, organic pork, special pork, pork-veal, organic pork-beef, mix FFPs, conventional poultry, organic poultry, seafood, and ready-to-eat FFPs

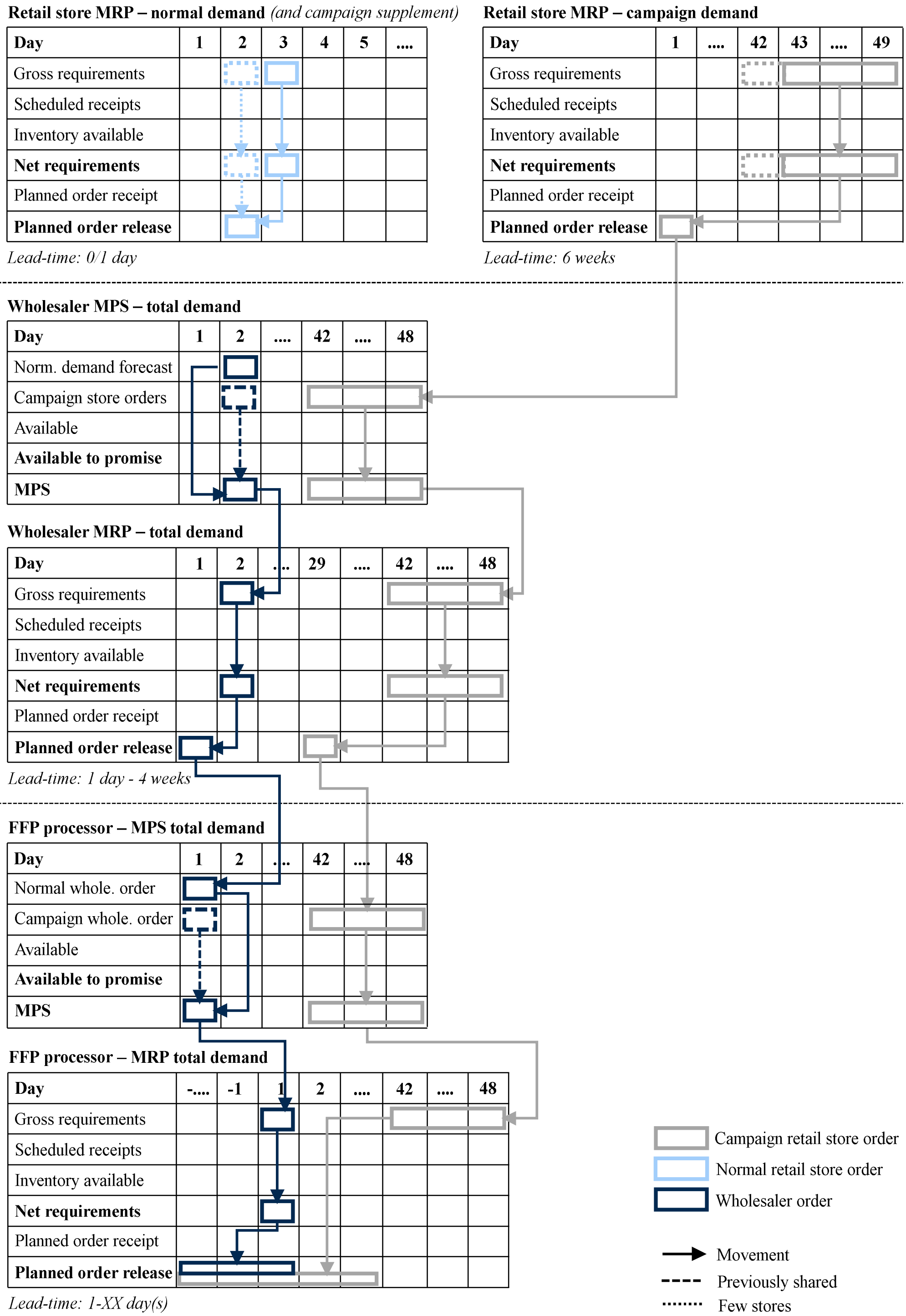
Figure 1 depicts the information sharing during the MRP and MPS decision-making at individual stages. It provides an understanding of when the demand information created at day one at the wholesaler is needed and created at the respective FFP processor and retail stores (explained below). The MPS at wholesaler represents the picking and packing and is only included to ensure a holistic understanding of the RP&C across the FFPSC. Two separate mainstreams of information are depicted representing two types of orders shared between retail store and wholesaler: the campaign demand information and normal demand information. Notice that the flows are combined to illustrate the interconnection between the two separate RP&C cycles (wholesaler – retail store and wholesaler – FFP processors), thus the processes are all relative to wholesaler's MRP decision at day 1. Hence, retail stores reflect future flows and FFP processors past flows.

For campaign demand, six weeks before delivery retail stores share campaign orders with the wholesaler according to gross requirements i.e. campaign orders for delivery at day 42-49 are shared at day 1 from stores. The wholesaler then schedules these for day 42-48 in MPS according-ly. Next, the wholesaler plans the replenishments through MRP for day 42-48 by aggregating, adjusting and sharing with the FFP processor four weeks before delivery (i.e. day 15). The FFP processor subsequently plans its MPS (for day 42-48) and accordingly orders raw material in MRP, a product dependent time in advance (day 2…41). This is marked grey in Figure 1. Hence, the campaign flow stretches across several weeks.

For normal demand, retail stores share so-called normal orders one day before delivery (i.e. day 2, when delivered at day 3). For some retail stores, the FFPs are picked and packed at wholesaler and delivered the same day as ordered, depending on the distribution setup, see dotted lines in stores' MRP (i.e. day 2, when delivered at day 2). If the stores have ordered too few FFPs in previously shared campaign orders, they may supplement the campaign quantities through the normal order. Thus, the normal order in the wholesaler's MPS contains normal and campaign de-mand) (marked light blue in Figure 1). The wholesaler then plans forecasted demand (marked dark blue), normal demand orders and supplementing campaign quantities (marked red) and controls previously sent campaign orders (marked blue dashed) in its MPS. This derives the net requirements for the MRP and releases a normal wholesaler order to the processor at day 1. The processor de-livers FFPs the same day as processing, and thus its net requirements may be released as processor's orders as late as the same day as processing. This is marked black in Figure 1.

All FFP processors receive the same type of demand information through electronic data inter-change (modality) during the same time period (timing). In addition to normal/campaign orders, the information includes annual product demand forecast shared once a year and campaign de-mand forecast at product level shared a few months in advance of the campaign.

Figure 1: Sharing of demand information during RP&C in the FFPSC



3.3. Data Collection & Analysis

Table 4 summarizes details about the data collection and its focus. Semi-structured interviews were used based on standardized questions (Yin 2014; Eisenhardt 1989), from February 2018 until February 2019. Three interview guides were created specifically for each SC stage. The interview guides were tested before actual interviews (Yin 2014), resulting in minor changes. One to three interviews were conducted with each case, each at a length of 2-2.5 hours and questions sent in advance. The interviews were recorded and analysed in more detail (Yin 2014). The first interview served to provide general information about the company, its roles and the planning and control processes. The second (and third) interview served to verify and approve findings from the first interview.

On-site observations and interviews allowed mapping of the entire transformation process from the creation of raw material at the farmer until selling in stores. First, a general SC map provided an understanding of all cases, the overall supply network and general product and information flow. Then, flow charts mapped the detailed product flows for each case. The store-maps were compared and generalised into one single flow chart to overcome certain differences in processes (e.g. physical way of replenishing shelves). Rough timepoints and deadlines were identified, e.g. how long time in advance of delivery at the retail stores different processes occur. Then, process maps highligted the decision-making processes during the wholesaler's RP&C, in relation to retail stores ordering (i.e. MRP) and the MRP and MPS at FFP processor (according to Figure 1) as well as the interconnectedness across the FFPSC. To obtain an even more detailed understanding of information use, sharing and output from decision processes, IDEF0 diagrams were used to model and analyse input, output, mechanism and control during decision making (see, e.g. Danese, 2007 and Barratt and Oliveira, 2001). The FFPSC map, charts and IDEF0 were compiled into one map for each processor and analysed in terms of the different PECs' impact on MRP and MPS at the processor.

Table 4: Data collection

Case study	Period	Data sources	Role of the interviewees	Focus of collection
Beef 1	Oct 2018, Nov 2018	2 interviews (1,5-2 hours), questionnaire, memos from meetings, annual report	sales responsible, production planner and scheduler	MRP, MPS, information sharing, PECs, processing stages
Beef 2	Oct 2018, Dec 2018	2 interviews (1,5 hours), questionnaire, factory tour, memos from meetings, company presentation, annual reports	senior sales manager, vice president	
Pork	Oct 2018, Dec 2018	2 interviews (1,5-2,5 hours), questionnaire, factory tour, memos from meetings, annual reports	sales director, customer care manager	
Poultry	Oct 2018, Dec 2018	2 interviews (1,5-2 hours), questionnaire, memos from meetings, annual reports	key account manager, supply chain manager, demand planner	
Fish	Dec 2018	1 interview (1,5 hours), questionnaire, memos from meetings	director	
Wholesaler	Mar 2016 until Dec 2018	4 interviews (1-2,5 hours), workshop, projects, memos from meetings, statistics and reports from BI, WMS, ERP systems, annual reports	COO, procurement officer, product manager, purchasing assistant, purchaser 1, 2 and 3, warehouse manager	RP&C, information sharing
Store 1	Feb 2018, Jan 2019	2 interviews (2-2.5 hours), questionnaire, memos from meetings, store material	franchisor	
Store 2	Feb 2018	1 interview (1.75 hours), questionnaire, memos from meetings	franchisor	
Store 3	Feb 2018	1 interview (2 hours), questionnaire, memos from meetings, store material, screenshots, statistics and reports from ERP systems	franchisor, meat-responsible	
Store 4	Feb 2018	1 interview (2 hours), questionnaire, memos from meetings, store material, screenshots	franchisor	
Store 5	Feb 2018	1 interview (2.5 hours), memos from meetings	franchisor	
Store 6	Feb 2018	1 interview (2.25 hours), questionnaire, memos from meetings	franchisor	
Store 7	Feb 2018	1 interview (1.75 hours), questionnaire, memos from meetings	franchisor	
Store 8	Feb 2018	1 interview (1.75 hour), memos from meetings, statistics and reports from ERP systems	franchisor	
Store 9	Feb 2018	1 interview (1.5 hours), questionnaire, memos from meetings, store material	franchisor, meat-responsible	

4. Analysis

4.1. Planning Environment Characteristics at FFP Processors

Table 5 summarizes the identified PECs with a brief explanation and indication of whether they impact directly the processor, or indirectly through the farmer. The PECs are classified according to their type and impact area, and compared across FFP processors. In total 29 PECs were identified; 28 for beef, 12 for fish, 21 for pork, and 15 for chicken. Ten PECs are shared across all FFP processors. While 12 PECs relate to MRP, 15 PECs relate to the MPS processes and two PECs to both. Particular processor-unique PECs related to MRP and MPS are described in the following.

The MRP at FFP processors. For MRP at Beef1 and Beef2, the raw materials are pushed from farmers to slaughtering without any option of reducing the flow, per se. The flow can only be stopped if an FFP processor cannot process the animal flow causing excessive inventories of materials (i.e. living animals). If receiving less raw material than planned, Beef1 may source cuts and pieces from Beef2. Given the inability of controlling incoming raw material flow and age-difference in cows, Beef2 pointed out the need for demand information in accordance to the total supply lead-time. Unlike Pork, Chicken and Fish, cow-meat is considered a by-product by farmers, and milk a primary product. Consequently, when milk-prices raise, supply of animals reduces, and vice versa. Also unique for Beef2, it operates with aged meat ("deluxe" product line) from South America with a latent longer supply lead-time and import restrictions at EU-level (so-called GATT-quotas). Depending on the total amount of meat sourced into EU, the available/allowable amount to source by Beef2 may in periods be high while in others low, and difficult to predict. Low flexibility in managing incoming raw material is same for Pork when including farmers and the slaughtering process. However, in this study, Pork orders pre-specified pork-cuts in their MRP that are to be further cut, mixed and processed. While Chicken orders living chickens ready for slaughtering and therefore pulls raw materials according to orders, Fish buys raw material daily on auctions. Seen in terms of supply lead-time, while some FFPs in principle require information sharing up to years in advance (e.g. beef meat) for their MRP, others suffice by sharing information at the day of processing (e.g. fish) since the sourcing is the same day.

The MPS at FFP processors. Beef1 and Beef2 utilize the most sophisticated processing setup, and hence a corresponding MPS, given the ongoing product funnelling and variation throughout processing, e.g. cutting and ageing. Oppositely other FFP processors, Beef1 and Beef 2 are characterised by inventories after almost every processing-stage, with storing for specific periods due to processing (e.g. cooling and de-boning, aging-periods of up to several weeks). Subsequently, they become the most flexible in terms of using buffers to meet fluctuating demand. Pork and Fish experience the most straightforward processing stages due to: ordering raw material according to specified criteria (e.g. specific primal cutting or with specific fat percentage), performing only secondary cutting (e.g. slicing pieces), and processing. Their MPS is hence not characterised by ageing/buffering, making both pork and fish more sensitive to forecasting/planning accuracy. Some PECs impact MPS in several processing stages, and certain ones may affect MRP/MPS differently, depending on meat type. As an example, "time of year, conformity" relates to the changes in percentage of fat and size of raw materials depending on the time of the year. Consequently, the availability of raw material for a given product may also change, influencing either MRP or MPS. Since ground beef products are restricted by fat percentage, but per se can be produced of any part of the animal (though at different cost), the change in conformity does not influence the processing but the availability of raw material for the product. Thus, it affects the MRP of raw material from farmers to produce ordered amounts.

Detailed mappings of the PECs impacting the processing stages at each FFP processor are provided in Appendix 1 (Figure A1, A2, A3 and A4).

Table 5: PECs impacting information needs per animal type

PEC	Type	Description	Beef	Pork	Chicken	Fish	Impact area
Ageing	Product	Depending on primal/sub-primal/secondary cutting and intended level of ageing of the final product, the meat may be stored for ageing up to several months before ready for packaging.	x				*MPS*
Animal lifetime	Supply	Breeding time until slaughtering differs from animal to animal and meat type to meat type. Information should be shared accordingly to ensure enough number of animals for slaughtering.	x	(x)	x	(x)	*MRP*
Campaign / promotion	Demand	In case of campaigns/ promotions, additional amounts of raw materials are required and well as larger quantities to be produced and processed, in turn influencing processing start. Follows "the-larger-campaign, the-more-in-advance" principle.	x	x	x	x	*MRP / MPS*
Dairy prices	Supply	Rising milk prices cause farmers to keep cows alive for a longer time, thus reducing amounts sent to slaughtering, i.e. availability of beef meat.	x				*MRP*
Delivery time	Supply	Time to transport meat from origin place/country to processing facility. Information should be shared accordingly to ensure availability.	x*	(x)		x	*MRP*
Import non-EU to EU	Supply	Import of non-EU meat to the EU is subject to GATT-quotas, restricting the amounts available in a year. The higher demand at the beginning of a period, the faster quotas are reached, resulting with variable and reduced availability	x**				*MRP*
Organic	Product / Supply	For organic meat, available quantities are generally lower than for conventional, requiring that information sharing may be shared earlier to ensure building up temporary storage of meat (including vacuuming).	x**	(x)	x		*MRP*
Opening for slaughtering	Production	Depending on when the slaughterhouse is working during the week, then to supply raw material for processing and processing, information may be shared differently, e.g. if closed during weekend yet with daily deliveries to the wholesaler.	x	(x)	x		*MPS*
Quantity stability	Demand	If a product is required in the same quantity constantly, no need for information sharing arises.	x	x	x	x	*MPS*

PEC	Type	Description	Beef	Pork	Chicken	Fish	Impact area
(Consecutive) processing capacity	Production	If the required capacity for a product/cutting in a given processing step exceeds max capacity in the preceding step, then the raw material is sourced from outside, requiring additional time.	x				*MRP*
Processing complexity	Product	Based on if a product is, e.g. marinated or mixed, certain quantity restrictions may apply for processing the meat and producing the FFPs.	x	x	x		*MPS*
Processing flexibility	Production	Depending on how much processing can change in quantity, updated information about quantities may be shared	x	x	x	x	*MPS*
Processing frequency	Production	Based on, e.g. internal scheduling, processing and shelf life, a product may be produced daily or only at different time points.	x	x			*MPS*
Processing scheduling	Production	Depending on when the processing is scheduled (and re-scheduled), updating of information may be favourable.	x	x	x	x	*MPS*
Product funnelling	Product	Depending on how many different FFPs can be made from a single meat cutting, different allowances for storing, ageing etc. applies.	x	(x)	(x)		*MPS*
Product life cycle	Product	Depending on whether a product is, e.g. new or to be phased out, different time-horizons applies for ensuring enough amounts of packaging material and meat to meet demand.	x	x	x	x	*MRP / MPS*
Product upgradeability	Product / Production	Depending on the extent to which a product may be downgraded (e.g. in terms of fat-%) influence scheduling of processing.	x	x			*MPS*
Scarcity of cuttings	Product / Production	Certain cuttings are only limited available in very few amounts per animal. This requires extra slaughtering immediately up to demand and (limited) stock building of meat-pieces.	x	(x)			*MPS*
Shelf life of cuttings	Product	The time that parts and cuttings can be stored before it must be processed ranges from, e.g. few days to more than one month, allowing small buffers to be built up for certain cuttings.	x	(x)	x	x	*MPS*
Shelf life of final product	Product	Depending on how short shelf life the final product has (days vs weeks vs months), buffers can be built up to meet fluctuations in demand.	x	x	x	x	*MPS*
Short period demand	Product	Certain cuttings are available throughout the year but only demanded during a short period. To meet demand, meat is, e.g. frozen from when demand ends and processes when the demand arises.	x				*MRP*

PEC	Type	Description	Beef	Pork	Chicken	Fish	Impact area
Slaughtering-decoupling	Production	Whether slaughtering and processing are inherently linked may influence the ability to source meat. If not linked, processing company may source meat pieces/cuts (according to specification) from multiple slaughterhouses, while if linked then what is available is pushed through processing.	x	x			*MRP*
Slaughtering hierarchy	Product / Supply / Production	Depending on where a product is in the slaughtering hierarchy, it may be unique and only limited available from a carcass or common and “unlimited” available from a carcass mainly restricted by costs of meat (e.g. ground FFPs).	x	(x)	x		*MPS*
Stability in meat-classification	Product	Quality and conformity of the meat may generally fluctuate across animals letting availability of prime vs secondary quality meat become uncertain. The more fluctuating, the greater uncertainty for the availability of individual parts and cuts.	x	(x)	x		*MRP*
Time of year, conformity	Supply / (Production)	Depending on the time of year, the animals are generally, e.g. more/less fat or larger/bigger, letting availability increase or decrease.	x	(x)		x	*MRP*
Time of year, holidays	Production	Depending on if around Christmas/ Easter/alike slaughtering and processing may start earlier than usual.	x	x	x	x	*MPS*
Time of year, meat type	Supply	Depending on the time of year, certain meat types/breeds are excessive while others are scarce and vice versa.	x			x	*MRP*
Weather, demand	Demand	The more unstable the weather is, the more increase in information sharing for weather-sensitive FFPs (e.g. grill sausages and steaks), hereunder both temperature, sun and humidity.	x	x	x	x	*MPS*
Weather, supply	Supply	Depending on, e.g. wind and temperature (thereby also nutrition in water), the available amount of raw material may be reduced, influencing the available amount of raw material to source. The more unsteady weather, the more possible farmers to source from.				x	*MRP*

Note: * = only for imported meat
** = only for Beef2
( ) = indirect impact

4.2. Planning Environment Characteristics' Impact on Information Sharing

Table 6 summarizes the findings on PECs' impact on information sharing facets, along their origin (literature/case study) and type. When a facet can have several alternative values, as with e.g. timing (R/H/D/W/M/Q/Y), the appropriate value depends on the individual product, and for the beef-group, also whether it is beef, cattle or veal. Information affected by e.g. "campaign/promotion" and "import from non-EU to EU" must be shared when needed. Other PECs, such as e.g. "meat-type" and "conformity", require information sharing only when they change during the year. While some information may be aggregated at daily/weekly/ monthly/quarterly/yearly level, other information may be aggregated at a characteristic-dependent level such as ageing. As an example, if a product is to age for 21 days, information must be accordingly in terms of timing and aggregation. Similarly, for processing frequency, in-formation must be aggregated and comply with the time between processing runs. Information should also be shared from processor to wholesaler. In case of, e.g. processing capacity, dairy prices and processing frequency, the processor should first share information with the wholesaler to ensure that demand information is corresponding to the available supply. Hence, the PECs en-tail a highly differentiated information sharing, with different timings, frequencies, and product dependent content. Consequently, information sharing should be related to different planning horizons. As example, for beef FFPs with more than 2 years animal lifetime and veal products with less than 10 months animal lifetime, the information shared should reflect respectively long- and medium-term time horizon, while reflecting short-term for chicken with 40 days lifetime.

Mainly related to time-horizon and timing for sharing information, Figure 2 provides an over-view of the PECs' given the information sharing' dynamism i.e. whether the PECs impact on in-formation sharing is constant (no dynamism), variable (a certain level of dynamism) or both. Certain PECs, such as animal' lifetime, availability of meat during the year, ageing periods, scarcities in meat cuts per animal, are constant through time with identical and consistent impact on MRP and MPS, thus also on information sharing. Other PECs' impact changes through time and are less predictable, such as dairy prices, import from non-EU to EU, weather' impact on supply, and pro-cessing frequency. Depending on this, information may need to be updated accordingly. As an example, when milk prices increase, the supply of meat decreases (almost) instantly, fostering information sharing when it occurs – and not at scheduled time points. Also, depending on how much the milk prices would increase, the impact may differ. With the frequency of sharing information spanning from real-time to annual information sharing (consequently influencing the frequency, i.e. aggregation level), it is evident that PECs' impact on information sharing differs across multiple different facets. The stretched boxes represent the time a certain PEC may span over in general (e.g. delivery time and opening for slaughtering), and the separated boxes with arrows the timespan from a product-dependent PECs.

Table 6: PECs' impact on demand information sharing facets

PEC	**Literature/Case study**	**Type of characteristic**	**Impacted area**	**Frequency**	**Timing** (sharing of information in advance)	**Direction** (in case of changes to characteristic)	**Modality** (way of sharing)	**Content** (type of information)	**Content** (aggregation of information)	**Content** (planning horizon)	**Dynamism** (variation in impact)
Ageing	C	P / Pr	MPS	O	W/M	W	EDI	F/O	ageing period	S	F
Animal lifetime	L	P	MRP	O	W/M/Q/Y	P	EDI	F	W/M/A	S/M/L	F
Campaign/Promotion	L	D	MRP / MPS	WN	D/W/M	W	EDI	F/O	D/W	S/M	V
Dairy prices	C	S	MRP	UC	W → M	P	EDI	F/O	D/W/M	S/M	V
Delivery time	L	S	MRP	O/ UC[1]	D → M	P	EDI	F/O	transport time / max. storage time	S	F
Import non-EU to EU	C	S	MRP	WN	W → Q	P	EDI	F	W/M	S	V
Organic	(L)C	P	MRP	O	D/W	P	EDI	F	D/W	S	F
Opening for slaughtering	L	Pr	MPS	O	W → Q	P	EDI	F	D/periodically	S	F
Quantity stability	L	D	MPS	O	W → Y	P	EDI	F	--	S	F
(Consecutive) processing capacity	L	S	MRP	O	D/W	P	EDI	F	D/W	S	F
Processing complexity	L	D / Pr	MPS	O	H/D	P	INT/EDI	F/O	time between		
Processing flexibility	L	Pr	MPS	O	R/H/D	P	INT/EDI	O/S	so far/D	E/S	V

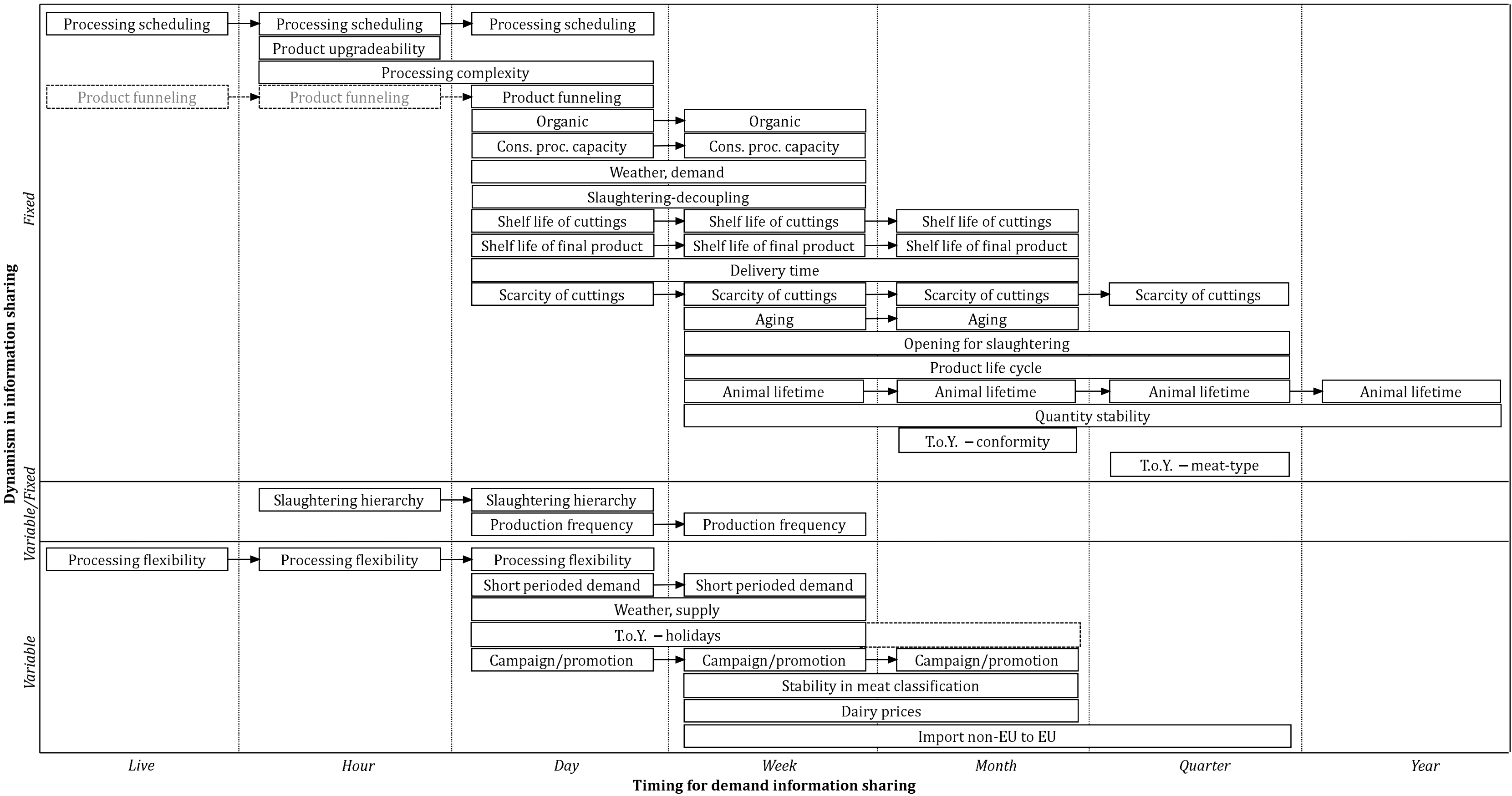
PEC	**Literature/Case study**	**Type of characteristic**	**Impacted area**	**Frequency**	**Timing** (sharing of information in advance)	**Direction** (in case of changes to characteristic)	**Modality** (way of sharing)	**Content** (type of information)	**Content** (aggregation of information)	**Content** (planning horizon)	**Dynamism** (variation in impact)
Processing frequency	L	Pr	MPS	WN	D → W	P	EDI	F/O	demand between processing runs	S	F/V
Processing scheduling	L	Pr	MPS	O	R/H/D	P(W)	INT/EDI	O(/S)	so far/D	E/S	F
Product funnelling	L	P	MPS	O	(R/H)/D	P	INT/EDI	O	so far/D/W/(M)	S	F
Product life cycle	L	P	MRP/MPS	UC	W → Q	W	EDI	F	D/W	S/M	F
Product upgradeability	C	P	MPS	O	H	P	INT	O/S	so far/D	S	F
Scarcity of cuttings	C	P/Pr	MPS	WN	D/W/M/Q	P	EDI	F/O	D/W/M	S	F
Shelf life of cuttings	L	P	MPS	O	D/W/M	P	EDI	F/O	D/W/M	S	F
Shelf life of final product	L	P	MPS	O	D/W/M	P	EDI	F/O	D/W	S	F
Short period demand	L	D	MRP	WN	D/W	W	EDI	F/O	D/W	S	V
Slaughtering-decoupling	L	Pr	MRP	O	D → W	P	EDI	F/O	D/W	S	F
Slaughtering hierarchy	(L) C	Pr	MPS	O	H/D	P	EDI	O/S	D/W	S	F/(V)
Stability in meat classification	C	S	MRP	WN	W → M	P	EDI	F	D/W	S	V
Time of year, conformity	C	S	MRP	UC	M	P	EDI	F	D/W	S	F
Time of year, holidays	(L) C	D/Pr	MPS	A	D → W(M)	P	EDI	F	D	S	V

PEC	**Literature/Case study**	**Type of characteristic**	**Impacted area**	**Frequency**	**Timing** (sharing of information in advance)	**Direction** (in case of changes to characteristic)	**Modality** (way of sharing)	**Content** (type of information)	**Content** (aggregation of information)	**Content** (planning horizon)	**Dynamism** (variation in impact)
Time of year, meat-type	C	S	MRP	UC	Q	P	EDI	F	D/W/M	S	F
Weather, demand	L	D	MPS	WN	D → W	W	INT/ EDI	F/O/S	so far/D/W	S	F
Weather, supply	C	S	MRP	WN	D → W	P	EDI	F/O	D/W	S	V

[1] if transport time fluctuates

Note: Literature/Case study: L = literature, C = case study
Type of PECs: P = product, D = demand, S = supply, Pr = production
Frequency: O = once, A = annually, WN = when needed, UC = upon changes
Timing: R = real-time, H = hour, D = day, W = week, M = month, Q = quarter, Y = year
Direction: W = wholesaler, S = supplier
Modality: EDI = Electronic Data Interchange, INT = internet/real-time tool
Content (type): F = forecast, O = order, S = sale
Content (aggregation): D = daily, W = weekly, M = monthly, A = annually
Content (planning horizon): E = execution, S = short-term, M = medium-term, L = long-term
Dynamism: F = constant (no dynamism), V = variable (dynamism)

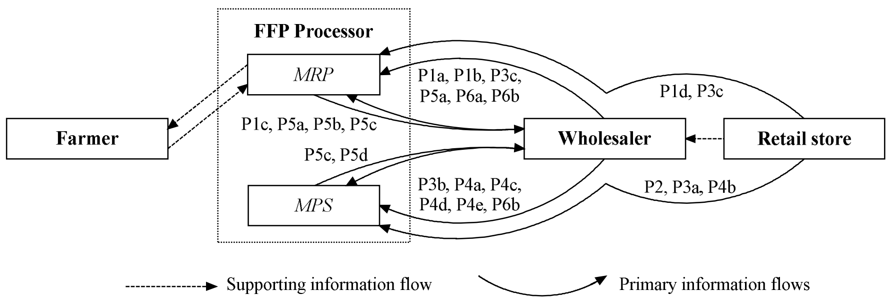
Figure 2: Timing for demand information sharing when complying with PECs



5. Discussion: Propositions for Demand and Supply Information Sharing

We abductively infer 19 propositions for ensuring effective information sharing considering how the observed PECs affect the information sharing facets. Figure 3 depicts which primary information flows the propositions belong to (full arrows) and the supporting information flows (dashed arrows) affecting the primary information flows. Certain propositions are listed twice as the flow depends on the context. The propositions have been grouped in 6 categories depending on the similarities in dominating PECs (Table 7). As an example, in propositions P1a-d animal lifetime, delivery time and ageing relate to the time it takes to source raw material (i.e. MRP), whether it is from farmers or from maturing/ageing place. Similarly, proposition P2 reflects the PECs related to the flexibility of the processing, P3 to the weather, and so forth. The next discusses the propositions.

Figure 3: Information flows for inferred propositions



5.1. Sourcing of Raw Material Propositions (P1a-P1d)

The animal life timespan vary from a few days to months or years. Since demand forecast deviations can only to limited level be absorbed by inventory due to deterioriation or limited space for storing live animal supply, creating forecast closer to actual decision making (MRP/MPS) im-proves the accuracy (Christensen, Steger-Jensen, and Dukovska-Popovska 2017). Two general supply lead-times were evident: long/short predictable and unknown/stochastic.

When total supply lead-time is predictable, the wholesaler would benefit from sharing demand forecast/order upstream according to processors' MRP. This timing may be fixed/scheduled. For long supply lead-time, e.g. beef, the processor may first plan and forecast demand (cf. farmer breeding animals) and later schedule/place order in MRP (cf. farmer shipping animals). For short supply lead-time, e.g. chicken, the forecast may only be shared once, or just, an order covering the growth time – depending on available information.

When total supply lead-time is unknown/stochastic, e.g. some beef and fish, buffers/inventories are typically built to withstand fluctuations (Chaudhary, Kulshrestha, and Routroy 2018). Storing impacts the quality relatively less for raw material/cuttings than for finished goods due to the additional processing (and less bacteria growth (Evans 2016)). Still, interest remains in ensuring effective MRP with as little storing as possible to provide the highest level of quality. Consequently, information sharing should be agile so that the wholesaler shares information upon de-mand from the FFP processor, i.e. when needed. An underlying assumption is that the FFP processor – just like the wholesaler – may not obtain information about sourcing options until the “last moment” of MRP. Also, the coverage period is not possible to determine, and thus demand information for the MRP should cover the period until the next delivery. In particular, fish are characterised by unknown/stochastic raw material supply lead-time and raw materials are delivered to FFP processors the same day as acquired/caught. In this situation, information about raw material availability is unknown until hours before delivery and processing at FFP processors. Since in-formation is needed so (relatively) late, the store orders may be available to wholesaler rather than forecasted demand. Propositions P1a-P1d (Table 7) reflect the effect of supply lead-time on in-formation sharing.

5.2. Processing Flexibility Proposition (P2)

All FFP processors reported different flexibility in the processing of products with few days shelf life. This is dependent on planning and scheduling constraints such as available raw material, pro-cessing schedule and available capacity (Fleischmann, Meyr, and Wagner 2015; Romsdal 2014; Entrup 2005), as well as the individual FFP, e.g. level of processing complexity, upgradeability and funnelling. For funnelling and upgradeability Beef1, Beef2 and Pork reported particularly high flexibility in processing ground FFPs. Consequently, sharing real-time demand information would allow adjusting the MPS and ongoing processing in real-time (Christensen, Mantravadi, et al. 2019). See Table 7 for Proposition P2.

5.3. Weather Propositions (P3a-P3c)

Weather impacts the demand and supply and thus MPS and MRP (e.g. Alftan et al. 2015; Taylor and Fearne 2009; Dreyer et al. 2018). This combined with freshness and availability requirement puts additional stress for effective information sharing. All FFP processors confirm this and de-scribe how differently and rapidly the weather impacts FFP demand. As an example, the demand for some FFPs is influenced by temperature, and for others by, e.g. amount of sunlight and wind. While cold/warm months are easier to forecast, demand fluctuations due to specific temperature range, sunshine and wind are more difficult to manage. Fish additionally reports about the particular impact of strong winds or storms on the supply of raw materials which, in the worst case, can lead to no catch. Timely and frequent information sharing is thus particularly important for MRP and MPS for both weather-sensitive demand and supply of FFPs. See Table 7 for Propositions P3a-P3c.

5.4. Shelf life and Undesired Aging Propositions (P4a-P4e)

Perishability has one of the most significant impacts on MPS at the FFP processor, whether for cuttings (WIP) or finished FFPs. With total shelf life ranging between weeks and a few days, it dictates the ability to have raw material/WIP buffers/inventories for meeting fluctuating demand (Christensen, Dukovska-Popovska, et al. 2019). In a similar vein, ageing also dictates MPS by requiring specified periods of storing before further processing/sale. For longer shelf life FFPs with high demand, it may even be appropriate to maintain stock-levels for meeting fluctuations. Depending on the shelf life, FFPs may be processed more/less frequently. While short shelf life FFPs are processed daily, FFPs with longer shelf life are typically processed at planned timepoints and less frequently. Consequently, the information sharing should reflect this by ensuring high forecasting accuracy, and for short shelf life FFPs, order update in case of changes in demand (particularly if less expected demand). See Table 7 for Propositions P4a-P4e.

5.5. Enforced Scarcity/Excess Propositions (P5a-P5d)

Four propositions are generated related to scarcity and excess of both raw material and final FFPs (See Propositions P5a-P5d in Table 7). Related to MRP, Beef1 reported quantity restrictions for sourcing raw materials into the EU. For FFPs with longer raw material/product shelf life, it makes sense to build up inventories in the FFPSC to ensure raw material/finished product supply, when quantities are close to not available. Therefore, sharing both availability information from processor to wholesaler, and after that updated order forecasts timely from wholesaler to processor (i.e. as event occurs), allows increasing raw material/product availability. Beef1 further reported the influence of dairy prices on raw material availability. As these FFPs have both longer and shorter shelf life, there is no per se option for building up inventories in MRP to ensure supply. Further, since changes in dairy prices are not always foreseeable, and the FFP processor has experience about the impact from farmers as well as options for sourcing elsewhere, increased information sharing from FFP processor to wholesaler must be according to when changes occur. The impact from these may additionally be enhanced during campaign/promotions.

Related to final FFPs, all processors reported limited processing capacity during specific periods in a year, influencing MPS. This is caused by two limitations: (1) when demand exceeds the maximum available processing capacity due to campaigns/promotions, slaughtering decoupling and/or (consecutive) processing capacity; (2) unavailable processing capacity due to opening hours, processing frequency or closing during holidays. To meet demand, it makes sense to build up inventories as part of the MPS to ensure supply, when capacity is not available. Therefore, sharing both availability information from processor to wholesaler and later updated order forecasts timely from wholesaler to FFP processor (as event occur) allows increasing availability.

5.6. Special Planning Environment Characteristics Propositions (P6a-P6b)

All processors reported FFPs with unique product characteristics, requiring additional attention in information sharing. Common for them is the mix of latent scarcity in availability and supply lead-time. As an example, organic chicken takes longer time than conventional ones to grow, and they are typically bred in smaller quantities, requiring earlier information sharing to ensure raw material availability as well as higher precision in order quantification. Both Beef1 and Beef2 reported FFPs that are only demanded a certain period of the year (alike seasonality). Further-more, for meat-cuttings with limited availability and subject for product funnelling, freezing them in advance of expected demand is done to ensure having enough supply. Consequently, demand information should be shared a sufficient time in advance as input to processors MRP to ensure enough frozen raw material.

All FFP processors mentioned the importance of the product life cycle stage and the im-portance of information sharing when any related change happens. In case of product introduction stage, the service level to the wholesaler (and retail stores) can be affected if demand increases and there is lack of raw material (meat trays, foil, labels, different ingredients/-mixes, etc.). When a product is in declining stage, the waste level at the processor can increase. Therefore, the whole-saler should share information upstream about any life cycle changes, according to the material' supply lead-time and/or batch size, enabling improved material/product availability. See Table 7 for Propositions P6a and P6b.

Table 7: Propositions for effective demand and supply information sharing, grouped by aggregated PECs

Area	#	Description	Related PECs
Sourcing of raw material	P1a	For FFPs using raw materials with long predictable total supply lead-time, the wholesaler would benefit from sharing demand forecast for the entire supply/growth/ageing-period (content) with the FFP processor (direction) when the FFP processor forecasts demand (timing), followed by an update of the demand forecast when the FFP processor schedules and releases order(s). Because of predictable supply lead-time, the timing may be fixed (i.e. frequency).	ageing, animal lifetime, delivery time
	P1b	For FFPs using raw materials with short predictable total supply lead-time, the wholesaler would benefit from sharing demand forecast, if possible, even order, for the entire supply/growth-period (content) with the FFP processor (direction) when the FFP processor schedules and releases order(s) (timing). Since the supply lead-time is predictable, the timing may be fixed (frequency).	
	P1c	For FFPs using raw materials with unknown/stochastic total supply lead-time, the wholesaler would benefit from sharing demand forecast covering the need until next delivery (content) with the FFP processor (direction) when it obtains information about raw material availability and releases its order (timing). Since unknown/stochastic supply lead-time, timing is indefinable and not possible to schedule, thus the wholesaler shares upon request from the FFP processor (frequency).	
	P1d	In addition to P1c, for raw material acquired the same day as processing and/or delivery, the wholesaler would benefit from sharing updated order information or retail store order (content) with the FFP processor (direction) when it sources raw material (timing). If overlapping retail stores opening hours, real-time retail store order (content) should be shared ongoingly (frequency) with order-determination upon FFP processor's request (timing) through (near-)real-time software such as internet (modality).	
Processing flexibility	P2	For FFPs with flexible processing quantities, the wholesaler would benefit from ongoingly (frequency) sharing real-time retail store order according to max tolerated deviations (content) with the FFP processor (direction) during the (adjustable) processing through (near-)real-time software such as internet (modality), with order-determination upon request from the FFP processor (timing).	processing complexity, product funnelling, product upgradeability, processing flexibility, processing scheduling, slaughtering hierarchy

Area	#	Description	Related PECs
Weather	P3a	For FFPs with weather sensitive demand in ongoing processing, the wholesaler would benefit from ongoingly (frequency) sharing real-time retail store order according to max tolerated deviations (content) with the FFP processor (direction) during the (adjustable) processing through (near-)real-time software such as, e.g. internet (modality), with order-determination upon request from the FFP processor (timing).	weather demand, weather supply
	P3b	For FFPs with weather sensitive demand not in ongoing processing, the wholesaler would benefit from sharing demand forecast (covering need until next delivery) (content) with the FFP processor (direction) when the FFP processor plans his processing (timing), followed by updated information when the FFP processor schedules the processing (frequency) – according to max tolerated deviations.	
	P3c	For FFPs with weather sensitive supply, the wholesaler would benefit from sharing updated demand forecast, or order, according to max tolerated deviations (content) with the FFP processor (direction) when he schedules and/or releases orders (timing). Qua P1c and P1d, information may represent real-time retail store order (content).	
Shelf life and undesired ageing	P4a	For FFPs with short shelf life which are processed daily and not yet in processing, the wholesaler would benefit from sharing demand forecast/order for the day, i.e. until next delivery according to retail store determined inventory levels (content) with the FFP processor (direction) when he schedules the processing (timing), followed by an update/order according to incoming retail store orders before processing starts (frequency).	ageing, processing frequency, shelf life of cuttings, shelf life of final product
	P4b	For FFPs which are processed daily and in processing, the wholesaler would benefit from ongoingly (frequency) sharing real-time retail store orders (content) according to max tolerated deviations and retail store determined inventory levels (content) with the FFP processor (direction) with final order-determination upon request from the FFP processor (timing) through (near-) real-time software such as, e.g. internet (modality).	
	P4c	For FFPs with short shelf life which are processed daily and with daily access to additional raw material which are yet to be scheduled, the wholesaler would benefit from sharing aggregated retail store order (content) with the FFP processor (direction) when retail stores close/immediately before he schedules processing (timing), followed by update upon FFP processor's request qua P4b when in processing (frequency).	

Area	#	Description	Related PECs
	P4d	For FFPs with longer shelf life/ageing processed daily, the wholesaler would benefit from allowing minimum inventory-building to withstand demand fluctuations and smoothen out the FFP processor's processing, thereby share demand forecast (covering the next day' demand) (content) with the FFP processor (direction) when he schedules the processing (timing).	
	P4e	For FFPs with longer shelf life/ageing which are not processed daily, the wholesaler would benefit from sharing demand forecast (covering need until next delivery) (content) with the FFP processor (direction) when he plans the processing (timing), followed by updated order when he schedules the processing (frequency) – in accordance with max tolerated deviations.	
Enforced scarcity/ excess	P5a	For FFPs where raw material is subject to unknown and latent scarcity, the FFP processor would benefit from sharing information about available quantities of raw materials (content) with the wholesaler (direction) when either significant changes to availability occur so the wholesaler can plan demand forecast (content) and share with the FFP processor (direction). Or, if close to scarcity limits, when the wholesaler plans orders (content) and shares with the FFP processor (timing). This should be followed by an update when scheduling the orders (frequency).	processing capacity, campaign/promotions, dairy prices, import non-EU to EU, opening for slaughtering, quantity stability, scarcity of cuttings, slaughtering-decoupling, stability in meat classification, time of year conformity, time of year holidays, time of year meat type
	P5b	For FFPs where raw material is subject to unknown and sudden scarcity/excess, the FFP processor would benefit from sharing information about changes and projected available quantities of raw materials (content) with the wholesaler (direction) when the change occurs (timing), so the wholesaler can plan orders (content) and share with the FFP processor (direction), followed by an update when the wholesaler schedules orders (frequency).	
	P5c	For FFPs with greater demand than processing capacity or raw material availability, the FFP processor would benefit from sharing information about available processing capacity or raw material availability (content) with the wholesaler (direction) when the wholesaler plans orders to the FFP processor (timing), so the wholesaler can plan and share orders and inventory levels accordingly (content) with the FFP processor (and potentially additional FFP processor) (direction). This should be followed by an update when scheduling the orders (frequency).	

Area	#	Description	Related PECs
	P5d	For FFPs subject to period(s) of unavailable processing capacity, the FFP processor would benefit from sharing information about this (content) with the wholesaler (direction) when either the periods are known to the FFP processor or the wholesaler plans orders to the FFP processor (timing), so the wholesaler can plan accordingly (content) with the FFP processor or an alternative FFP processor if needed (direction). This should be followed by an update when scheduling the orders (frequency).	
Special PECs	P6a	For FFPs with greater demand than raw material (adjustable) supply, the wholesaler would benefit from sharing demand forecast (content) with the FFP processor (direction) in accordance with supply lead-time - when facing a by-the-wholesaler-set significant chance of risking unavailability of raw material (timing), followed by an update when the wholesaler plans and/or schedules orders (frequency).	organic, product life cycle, short period demand
	P6b	For FFPs changing stage in the product life cycle, the wholesaler would benefit from sharing last expected demand date and demand forecast (content) with the FFP processor (direction) in accordance with a by-the-processor-set time point equal to supply lead-time (timing), followed by an update when the wholesaler plans and/or schedules orders (frequency).	

5.7. Propositions in relation to information sharing facets

In literature, sharing and creating joint forecast and orders is part of the collaborative supply chain. But the timing is processing- rather than sourcing-dependent (Thomé, Hollmann, and do Carmo 2014; Whipple and Russell 2007; Danese 2007), ranging from few weeks to one month in advance (Småros 2007). The forecast may be frozen and then later transformed into committed order(s) or replaced by updated order(s) a few days in advance (Alftan et al. 2015; Panahifar et al. 2015; Fang Du et al. 2009; Hollmann, Scavarda, and Thomé 2015). Further, RP&C practices (thus, information sharing) are demand-dependent. As an example, collaborative planning, forecasting and replenishment (CPFR) (VICS 2010) and collaborative buyer-managed forecasting (CBMF) (Alftan et al. 2015) are suggested for exceptions/promotional/campaign items with (smaller) demand deviations due to the intensive use of resources in forecast/order creation and evaluation (Danese 2007; Barratt and Oliveira 2001; Alftan et al. 2015). Many FFPs are everyday products with high/low demand deviations. Thus, sharing information according to MRP and MPS allows the FFPSC to synchronize the information and balance expectations and plans for future demand, while considering e.g. campaign plans and/or raw material availability. The propositions reflect this across all information sharing facets while being MRP-/MPS-contingent, resulting in six different flows (illustrated in Figure 3).

For content, the literature suggests sharing inventory availability and orders with a (static) coverage period, usually reflecting the time until next delivery – and that this may need to be customized (Kembro and Näslund 2014) and vary across, e.g. context (Kembro, Selviaridis, and Näslund 2014), partners (Simatupang and Sridharan 2005b) and aggregation levels (Watabaji et al. 2016). We confirm and detail this by specifying further that e.g. animal' lifetime, delivery time and age-ing impose a product-specific impact on the coverage period, e.g. growth time of raw materials. The study further entails varying and dynamic coverage period according to the PECs, since, e.g. growth time of raw materials may vary throughout the year. Extending current literature, we also see that certain PECs differ so significantly across FFPs that even real-time retail store demand is beneficial to ensure as close-to-real demand signal as possible. While content is general and uni-form/static through time in literature (for all products, a forecast-based order) this study shows that the closer to processing the information is shared, the higher requirements for real-time in-formation and product-level differentiation.

For timing and frequency, the literature suggests unscheduled or scheduled sharing (Ding et al., 2014; Ha, Park, and Cho, 2011) at different time points before replenishment (Kaipia et al. 2017). These time points may be when facing exceptions or internally triggered (e.g. when sending an order). Literature fails to provide otherwise clear guidelines as to when one is in favour of the other, and when to share, e.g. real-time. This study shows that real-time sharing may be beneficial for (weather-sensitive) FFPs in processing or when the raw material is sourced the same day as pro-cessing. Moreover, timing may be upon a request from FFP processors (i.e. unscheduled) accord-ing to specified rules such as when there is a certain risk, e.g. unavailability of raw materials, following max/min allowed boundaries for deviations. Here, the FFP processor informs the whole-saler about this, and the wholesaler shares demand information. This risk may be set precisely by the wholesaler, e.g. when there is a 20% chance of raw material stock-out, to allow hedging of raw materials or sourcing. While literature tends to present a static view on information sharing, de-spite recognizing the need to timely sharing (Xu, Dong, and Xia, 2015; Simatupang and Sridharan, 2005a), certain PECs entail that a variation in the frequency and timing at product-dependent level is beneficial. This is illustrated in Figure 2 and Table 7 (e.g. processing flexibility and time of year for supply). Thereby it circumvents the challenges from inappropriate timing and frequency (e.g. Xu, Dong, and Xia 2015; Chen, Wang, and Yen 2014). Also, it encompasses infor-mation"freshness" (hence validity) due to, e.g. reduced uncertainty and noise (Xu, Dong, and Xia, 2015; Chen, Wang, and Yen, 2014) as well as the FFPs' particular sensitivity to timely and fre-quent information sharing (Nakandala, Samaranayake, and Lau, 2017; Lusiantoro et al., 2018).

For direction, the literature mainly suggests sharing upstream in serial linkage or two-ways sharing dependent on the collaboration in the RP&C practice (VICS 2010; Alftan et al. 2015; Pramatari and Miliotis 2008). The study points out that certain PECs entail that the FFP processor initiates the demand information sharing from wholesaler. In case of enforced scarcity, for exam-ple, the FFP processor initiates the sharing by providing information about, e.g. availability or inventory level. In this way, the propositions add to the current understanding of either down-stream or mutually initiated demand information sharing.

For modality, the literature suggests information to be shared through a variety of different means, enhanced by the technological advancement. Although traditional means of sharing lead to smoother flow given their relatively increased acceptability, ease of use and lower costs (Watabaji et al. 2016) it is "critical to determine the specific means of sharing for each piece of information and establish the proper exchange architecture" (Kembro, Selviaridis, and Näslund 2014, 612). Internet-based information sharing tends to be a hyped modal choice in RP&C (Pramatari and Miliotis, 2008; VICS, 2004; Choi and Sethi, 2010; Marquès et al., 2010). However, the studies seem not to differentiate internet-based information sharing across FFPs. Instead, modality is cho-sen generically for the selected RP&C practice. From this study, it seems that modality is the least impacted information sharing facet with only few PECs driving real-time/internet-based information sharing. This relates particularly to when dealing with short-shelf life FFPs or ongoing processing where quantities may be adjusted.

5.8. Propositions in relation to planning environment characteristics

The literature recognizes PECs' relevance and importance for operations planning and control (Olhager and Rudberg, 2002; Dreyer et al., 2018; Jonsson and Mattsson, 2003; Alftan et al., 2015). However, although studies even provide optimization-based consideration of different PECs in MPS (Romsdal, 2014; Entrup, 2005), they take an internal processor view, rather than supply chain view. Also, the literature fails to provide PEC-specific guidance about e.g. when to share information in order for FFP processors to do MRP effectively. This study identifies 29 PECs with (in-)direct impact on information sharing, and provide guidance on if and how they differ across FFP processors. Product life cycle, campaign/promotions, weather demand and shelf life of final product seem universal product-/demand-related PECs, while time of year holiday, processing scheduling and processing flexibility seem to be universal production-characteristics. Arguably, this is due to their non-existent –at least very low – relation to product specific situations. As ex-ample, time of year holiday reflects certain restrictions on national scale (often labor union en-forced), e.g. closed at Christmas eve. Although this is obviously country-dependent, it is still im-posed on a national scale, and thus uniform when FFP processors are in the same country – which may be assumed due to the short shelf life, i.e. requirements for short distance in transport.

Other PECs are only relevant for FFP processors where the breeding/growth is not controlled by the farmer/FFP processor. As an example, weather supply affect seafood processors, since conditions in nature has a direct impact on raw material availability. This is similar for the processing capacity which appear to be relevant when FFP processors experience bottlenecks. Also here, the literature tends to provide optimization-based solutions from an internal point of view, without further multi-site information sharing, unless within same cooperation (i.e. one firm has multiple processing sites/lines). This study generates propositions reflecting dual-/multi-sourcing when relevant, ensuring that the information sharing splits in relevance and accordance to wholesaler' RP&C and contingent on FFP processors MPS/MRP.

Current literature differs the PECs across their intrinsic type, i.e. prod-uct/demand/supply/production but fails to provide a more detailed understanding as to how information sharing for the MRP vs MPS is impacted. From an overall view, this study groups the PECs as to whether they affect MRP, MPS or both, and details current understanding to product-level. More specifically, although lead-time has been considered a relevant PEC from an internal processing perspective (Romsdal, Strandhagen, and Dreyer 2014) and from a (raw material) sup-ply perspective (Dreyer et al. 2018), there has been lack of understanding in how it impacts information sharing facets and effective sharing at product-level in triadic FFPSC. This study extends current literature about how the delivery time in MRP affects the information sharing facets. It raises notion to its relevance in terms of MPS due to the already short lead-time from processing to delivery in stores, since otherwise not reported by FFP processors when long lead-time. The PECs related to shelf life (of cuttings and final products) appear to be predominant as opposed to processing lead-time. Since the fundamental intrinsic perishability of FFPs entails fast handling with no storing (for final products), processing lead-time seem excessive. Similar for MPS, this study also extends current literature by expanding e.g. "BOM complexity" (Jonsson and Mattsson, 2003; Spenhoff et al., 2014; Wänström and Jonsson, 2006) into more detailed PECs, such as e.g. slaughtering hierarchy (MPS), ageing (MPS), product upgradeability (MPS) and slaughtering decoupling (MRP), as well as supplementary PECs such as e.g. stability in meat-classification (MRP), time of year conformity (MRP) and time of year meat type (MRP). This divergent approach to (i.e. more detailed and MRP/MPS specific) allows to encompas what was initially BOM complexity in a more effective manner since allowing to determine the appropriateness across FFPs.

Finally, this study highlights externally enforced factors such as e.g. dairy prices and import regulations as PECs to consider when ensuring enough raw material availability (MRP) – as well as scarcity of cuttings and product upgradeability (MPS). Thereby also to include during RP&C at wholesaler. Although these PECs seem meat-type dependent, they provide a new nuanced view upon how information should be shared. No current study has defined these PECs across different FFPs. Further, the conformity of raw material has from a wholesaler perspective been understood as supplier-error-related consequences from e.g. batch of lower quality and thus considered subject for return/waste for the given FFP. I.e. conformity has enfolded as unavailability (i.e. reduced delivery performance) and otherwise accounted for by buffering and keeping inventories in the RP&C (when shelf life permits). This study provides a different ontological stance in that conformity is a natural part of living animals which must be accounted for. This by adjusting the MRP and MPS accordingly and further the RP&C. Hence, instead of wholesaler considers a given FFP as unavailable and buffers against this in the next order, the orders on other FFPs (where the given raw material may then be suitable for) may be adjusted according to the consequent in-creased availability as raw material for the other FFPs (following the different levels of cutting and processing complexity).

6. Conclusion

This paper investigated demand and supply information creation and sharing in the FFPSC during wholesaler's RP&C. It explored the PECs affecting FFP processor's MRP and MPS and subsequently the requirements set forth to information sharing. A multiple case-study with rigorous interview protocols at five different FFP processors (beef, pork, chicken and fish) led to abductively inferred propositions.

Very few papers have investigated PECs influence on information sharing, and no found study covers how the PECs affect the facets of information sharing considering the individual FFPs. Twentynine product-, production-, demand- and supply-PECs were identified, concerning the pro-cessing of FFPs i.e. MPS (15), sourcing of raw materials i.e. MRP (12) and a mix of both MRP and MPS (2).

It was identified, when, how and where each PEC sets forth requirements to the frequency, timing, direction, modality, content and dynamism of information sharing – contingent on the MRP and MPS. Based upon the PECs' similarities in impact, nineteen propositions were inferred relating to: sourcing of raw material (4), processing flexibility (1), weather (3), shelf life and undesired ageing (5), enforced scarcity/excess (4) and special PECs (2). Each, reflecting the need for sharing information from (retail store to) wholesaler to FPP processors. Certain information shar-ing must be initiated by the FFP processors to wholesaler, in order to determine the timing. This explicitates that the information provided by the farmer may provide the basis for FFP processor's timing and frequency of sharing.

The study adds to the current literature on PECs (e.g. Olhager and Rudberg, 2002; Jonsson and Mattsson, 2003; Alftan et al., 2015) by empirically verifying the PECs in different FFPSCs and identifying 12 new PECs. The study adds to information sharing literature by clarifying how the PECs' impact on FFP processors' MRP and MPS affect the information sharing during wholesaler's RP&C. Thereby overcoming both the product-specific focus on optimized planning (e.g. Romsdal, 2014; Entrup, 2005) as well as non-specific focus on different planning areas (e.g. Ivert et al., 2015; Dreyer et al., 2018; Alftan et al., 2015).

The study has managerial implications related to differention of the information sharing at a more detailed level. Sharing information during the RP&C of a single product may be impacted by several (or even all) PECs, leading to different requirements in terms of (mainly) frequency, timing and content. It is suggested that then, the practitioner chooses and evaluates the propositions as to their importance, and from this apply the propositional direction. In doing so, similarities of the individual PECs are reflected while not interfering and counter-affecting other PECs. Also, there are implications related to modality (i.e. real-time sharing). While information sharing in real-time certainly improves the content it stresses the IT-systems due to the heavy data trans-fer. Also, when applied across all products it may cause unnecessary investments in IT equip-ment/tools. This, since only a fraction of the assortment requires real-time sharing. Thus, while this study ignores financial aspects related to IT-investments and pressure on IT-systems, the practitioner should investigate its internal options for conveying real-time sharing. Alternatively, the information sharing may be at the "next-best" level, e.g. instead of real-time, hourly or daily information sharing may also contribute to performance.

Although multiple cases have provided rich and exploratory information from the FFP context, the study has certain limitations. Overarchingly, the study neither provides empirical validation and testing of the propositions in real-life context, nor any reflection of other relevant aspects such as costs associated with the propositions (e.g. resource consumption and investment in IT structure). The study does not provide comparison of how/when benefits exceed the associated costs for the individual propositions (thereby clarifying if some propositions provide more value than others). Fundamentally, the study relies on explorative interviews with one or a few person(s) from each case. This has been accounted for to some extent by ensuring that the nine studied re-tailers had enough common knowledge. However, the dispersion and difference in knowledge in each store limits the generalizability in the propositions and entails a latent premise about similar levels of skills and knowledge required. Also, although key-employees at the FFP processors and the wholesaler were interviewed, valuable information may unintentionally have been left out about e.g. the detailed processing of raw materials (from e.g. blue-colour workers at FFP processors), raw material breeding (from farmers) or assortment changes (from wholesaler). Further, there are limitations as not all FFP processors were interviewed, limiting the information about e.g. the slaughtering process for pork meat products, or other types of FFPs processed from living animals (e.g. exotic animals or turkeys). Further, choosing the most sold FFPs may have delimited other (less sold/unique) FFPs with potentially different processing may have been left out, i.e. different PECs and degree of importance. Also, the scope of MRP and MPS may have influenced the generation of propositions since not including other planning aspects, e.g. resource planning, sales and operations planning and demand management.

For future research, this study should be widened with more case studies on more and different FFPs such as e.g. fruits and vegetables, bread, dairy, fresh meals, medicine or blood to strengthen the findings on how PECs affect information sharing across the FFPSC during RP&C. As exam-ple, fruits and vegetables have a different growth period which is to a greater extent influenced by weather and regional temperature conditions (e.g. some fruits/vegetables are produced multiple places in the World). It would be interesting also to investigate if any difference exists in information sharing in other organisational constellations than franchise-based retailing. A franchise based structure entails decentralized RP&C with the individual store responsible for order-sizing, oppositely corporately owned retail stores with centralized RP&C. Also, it would be interesting to empirically test the propositions to quantify and generalise the actual impact on FFPSC performance such as e.g. stock-outs and waste versus the incremental increase in costs for sharing in-formation according to PECs.

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References

Alftan, Annika, Riikka Kaipia, Lauri Loikkanen, and Karen Sepns. 2015. "Centralised Grocery Supply Chain Planning: Improved Exception Management." *International Journal of Physical Distribution & Logistics Management* 45 (3): 237–259. doi:DOI 10.1108/IJPDLM-05-2013-0155.

Baihaqi, Imam, and Amrik S. Sohal. 2013. "The Impact of Information Sharing in Supply Chains on Organisational Erformance: An Empirical Study." *Production Planning and Control* 24 (8–9): 743–758. doi:10.1080/09537287.2012.666865.

Barratt, Mark, Thomas Y. Choi, and Mei Li. 2011. "Qualitative Case Studies in Operations Management: Trends, Research Outcomes, and Future Research Implications." *Journal of Operations Management* 29 (4): 329–342. doi:10.1016/j.jom.2010.06.002.

Barratt, Mark, and Adegoke Oke. 2007. "Antecedents of Supply Chain Visibility in Retail Supply Chains: A Resource-Based Theory Perspective." *Journal of Operations Management* 25 (6): 1217–1233. doi:10.1016/j.jom.2007.01.003.

Barratt, Mark, and Alexander Oliveira. 2001. "Exploring the Experiences of Collaborative Planning Initiatives." *International Journal of Physical Distribution & Logistics Management* 31 (4): 266–289.

BlueYonder. 2017. *Customer Experience in Grocery Retail: The Fresh Opportunity Customers in Fresh - A Global Survey of 4,000 Consumers Shine Light on Customer Experience in Fresh and Product Availability*.

Bozarth, Cecil C., Donald P. Warsing, Barbara B. Flynn, and E. James Flynn. 2009. "The Impact of Supply Chain Complexity on Manufacturing Plant Performance." *Journal of Operations Management* 27 (1): 78–93. doi:10.1016/j.jom.2008.07.003.

Broekmeulen, Rob A.C.M., and Karel H. van Donselaar. 2017. "Quantifying the Potential to Improve on Food Waste, Freshness and Sales for Perishables in Supermarkets." *International Journal of Production Economics*, no. October. Elsevier Ltd: 1–9. doi:10.1016/j.ijpe.2017.10.003.

Cai, Shaohan, Minjoon Jun, and Zhilin Yang. 2010. "Implementing Supply Chain Information Integration in China: The Role of Institutional Forces and Trust." *Journal of Operations Management* 28 (3): 257–268. doi:10.1016/j.jom.2009.11.005.

Cao, Mei, and Qingyu Zhang. 2011. "Supply Chain Collaboration: Impact on Collaborative Advantage and Firm Performance." *Journal of Operations Management* 29 (3). Elsevier B.V.: 163–180. doi:10.1016/j.jom.2010.12.008.

Carr, Amelia S, and Hale Kaynak. 2007. "Communication Methods, Information Sharing, Supplier Development and Performance: An Empirical Study of Their Relationships." *International Journal of Operations & Production Management* 27 (4): 346–370.

Chaudhary, Vaibhav, Rakhee Kulshrestha, and Srikanta Routroy. 2018. "State-Of-the-Art Literature Review on Inventory Models for Perishable Products." *Journal of Advances in Management Research2* 15 (3): 306–346.

Chen, Jengchung V., Chen Lin Wang, and David C. Yen. 2014. "A Causal Model for

Supply Chain Partners Commitment." *Production Planning and Control* 25 (9): 800–813. doi:10.1080/09537287.2013.764578.

Choi, Tsan Ming, Jian Li, and Ying Wei. 2013. "Will a Supplier Benefit from Sharing Good Information with a Retailer?" *Decision Support Systems* 56 (1). Elsevier B.V.: 131–139. doi:10.1016/j.dss.2013.05.011.

Choi, Tsan Ming, and Suresh Sethi. 2010. "Innovative Quick Response Programs: A Review." *International Journal of Production Economics* 127 (1). Elsevier: 1–12. doi:10.1016/j.ijpe.2010.05.010.

Chopra, Sunil, and Peter Meindl. 2010. *Supply Chain Management: Strategy, Planning and Operation*. New Jersey: Pearson.

Christensen, Flemming M. M., Iskra Dukovska-Popovska, and Kenn Steger-Jensen. 2017. "Differentiated Demand and Supply Chain Planning of Fresh Meat Products: Linking to Animals' Lifetime." In *Advances in Production Management Systems, The Path to Intelligent, Collaborative and Sustainable Manufacturing - Proceedings, Part II*, 139–147.

Christensen, Flemming M. M., Kenn Steger-Jensen, and Iskra Dukovska-Popovska. 2017. "Product Characteristics for Differentiated Replenishment Planning of Meat Products." In *International Symposium of Logistics, ISL*, 594–601. Ljubljana.

Christensen, Flemming M M, Iskra Dukovska-Popovska, Casper S. Bojer, and Kenn Steger-Jensen. 2019. "Asymmetrical Evaluation of Forecasting Models through Fresh Food Product Characteristics." In *Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part II*, edited by Farhad Ameri, Kathryn E. Stecke, Gregor von Cieminski, and Dimitris Kiritsis, 155–163. Springer.

Christensen, Flemming M M, Soujanya Mantravadi, Iskra Dukovska-Popovska, Hans-Henrik Hvolby, Kenn Steger-Jensen, and Charles Møller. 2019. "Horizontal Integration in Fresh Food Supply Chain." In *Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part II*, edited by Farhad Ameri, Kathryn E. Stecke, Gregor von Cieminski, and Dimitris Kiritsis, 164–172. Springer.

Danese, Pamela. 2007. "Designing CPFR Collaborations: Insights from Seven Case Studies." *International Journal of Operations & Production Management* 27 (2): 181–204. doi:10.1108/01443570710720612.

Dimitriadis, N. I., and S. C.L. Koh. 2005. "Information Flow and Supply Chain Management in Local Production Networks: The Role of People and Information Systems." *Production Planning and Control* 16 (6): 545–554. doi:10.1080/09537280500112397.

Ding, Ming Juan, Ferry Jie, Kevin A Parton, and Margaret J Matanda. 2014. "Relationships between Quality of Information Sharing and Supply Chain Food Quality in the Australian Beef Processing Industry." *International Journal of Logistics Management* 25 (1): 85–108. doi:10.1108/IJLM-07-2012-0057.

Dreyer, Heidi Carin, Kasper Kiil, Iskra Dukovska-Popovska, and Riikka Kaipia. 2018. "Proposals for Enhancing Tactical Planning in Grocery Retailing with

S&OP." *International Journal of Physical Distribution & Logistics Management* 48 (2): 114–138. doi:DOI 10.1108/IJPDLM-05-2013-0155.

Eisenhardt, K. M. 1989. "Building Theories from Case Study Research." *Academy of Management Review* 14 (4): 532–550. doi:10.2307/258557.

Entrup, Matthias Lütke. 2005. *Advanced Planning in Fresh Food Industries, Integrating Shelf Life into Production Planning*. Berlin: Physica-Verlag Heidelberg.

Eriksson, Mattias, Ingrid Strid, and Per-Anders Hansson. 2014. "Waste of Organic and Conventional Meat and Dairy Products — A Case Study from Swedish Retail." *Resources, Conservation and Recycling* 83. Elsevier B.V.: 44–52. doi:10.1016/j.resconrec.2013.11.011.

Evans, J. 2016. "Effects of Food and Beverage Storage, Distribution, Display, and Consumer Handling on Shelf Life." In *The Stability and Shelf Life of Food*, edited by Persis Subramaniam, 2nd ed., 107–140. Cambridge: Woodhead Publishing.

Fang Du, Xiao, Stephen C. H. Leung, Jin Long Zhang, and K. K. Lai. 2009. "Procurement of Agricultural Products Using the CPFR Approach." *Supply Chain Management: An International Journal* 14 (4): 253–258. doi:10.1108/13598540910970081.

Fawcett, Stanley E., Paul Osterhaus, Gregory M. Magnan, James C. Brau, and Matthew W. McCarter. 2007. "Information Sharing and Supply Chain Performance: The Role of Connectivity and Willingness." *Supply Chain Management* 12 (5): 358–368. doi:10.1108/13598540710776935.

Ferguson, Mark E., and Michael E. Ketzenberg. 2006. "Information Sharing to Improve Retail Product Freshness of Perishables." *Production and Operations Management* 15 (1): 57–73.

Ferguson, Mark E., and Oded Koenigsberg. 2007. "How Should a Firm Manage Deteriorating Inventory?" *Production and Operations Management* 16 (3): 306–321.

Fleischmann, Bernhard, Herbert Meyr, and Michael Wagner. 2015. "Advanced Planning & Structure of Advanced Planning Systems:" In *Supply Chain Management and Advanced Planning*, edited by Hartmut Stadtler, Christoph Kilger, and Herbert Meyr, 5th ed., 81–106. New York: Springer Berlin Heidelberg.

Flynn, Barbara B., Sadao Sakakibara, Roger G. Schroeder, Kimberly A. Bates, and E. James Flynn. 1990. "Empirical Research Methods in Operations Management." *Journal of Operations Management* 9 (2): 250–284. doi:10.1016/0272-6963(90)90098-X.

Fredriksson, Anna, and Kristina Liljestrand. 2015. "Capturing Food Logistics: A Literature Review and Research Agenda." *International Journal of Logistics Research and Applications* 18 (1): 16–34. doi:10.1080/13675567.2014.944887.

Gustavsson, Mattias, and Carl Wänström. 2009. "Assessing Information Quality in Manufacturing Planning and Control Processes." *International Journal of Quality and Reliability Management* 26 (4): 325–340.

doi:10.1108/02656710910950333.
Ha, Byoung-Chun, Yang-Kyu Park, and Sungbin Cho. 2011. "Suppliers' Affective Trust and Trust in Competency in Buyers, Its Effect on Collaboration and Logistics Efficiency." *International Journal of Operations & Production Management* 31 (1): 56–77.
Hollmann, Roberto Luis, Luiz Felipe Scavarda, and Antônio Márcio Tavares Thomé. 2015. "Collaborative Planning, Forecasting and Replenishment: A Literature Review." *International Journal of Productivity and Performance Management* 64 (7): 971–993. doi:10.1108/IJPPM-03-2014-0039.
Huang, George Q., Jason S.K. Lau, and K. L. Mak. 2003. "The Impacts of Sharing Production Information on Supply Chain Dynamics: A Review of the Literature." *International Journal of Production Research* 41 (7): 1483–1517. doi:10.1080/0020754031000069625.
Hübner, Alexander H., Heinrich Kuhn, and Michael G. Sternbeck. 2013. "Demand and Supply Chain Planning in Grocery Retail: An Operations Planning Framework." *International Journal of Retail & Distribution Management* 41 (7): 512–530. doi:10.1108/IJRDM-05-2013-0104.
Hung, Wei Hsi, Chin Fu Ho, Jau Jeng Jou, and Yi Ming Tai. 2011. "Sharing Information Strategically in a Supply Chain: Antecedents, Content and Impact." *International Journal of Logistics Research and Applications* 14 (2): 111–133. doi:10.1080/13675567.2011.572871.
Ivert, Linea Kjellsdotter, Iskra Dukovska-Popovska, Riikka Kaipia, Anna Fredriksson, Heidi Carin Dreyer, Mats I. Johansson, Lukas Chabada, Cecilie Maria Damgaard, and Nina Tuomikangas. 2015. "Sales and Operations Planning: Responding to the Needs of Industrial Food Producers." *Production Planning & Control* 26 (4). Taylor & Francis: 280–295. doi:10.1080/09537287.2014.897769.
Jonsson, Patrik, and Jan Holmström. 2016. "Future of Supply Chain Planning: Closing the Gaps Between Practice and Promise." *International Journal of Physical Distribution & Logistics Management* 46 (1): 62–81. doi:10.1108/IJPDLM-05-2015-0137.
Jonsson, Patrik, and Sitg-Arne Mattsson. 2003. "The Implications of Fit between Planning Environments and Manufacturing Planning and Control Methods." *International Journal of Operations & Production Management* 23 (8): 872–900. doi:http://dx.doi.org/10.1108/MRR-09-2015-0216.
Jonsson, Patrik, and Stig-Arne Mattsson. 2013. "The Value of Sharing Planning Information in Supply Chains." *International Journal of Physical Distribution & Logistics Management* 43 (4): 282–299.
Jonsson, Patrik, and Paulina Myrelid. 2016. "Supply Chain Information Utilisation: Conceptualisation and Antecedents." *International Journal of Operations & Production Management* 36 (12): 1769–1799. doi:http://dx.doi.org/10.1108/MRR-09-2015-0216.
Kaipia, Riikka, Jan Holmström, Johanna Småros, and Risto Rajala. 2017. "Information Sharing for Sales and Operations Planning: Contextualized Solutions and Mechanisms." *Journal of Operations Management* 52: 15–29.

Kehoe, D.F., and N.J. Boughton. 2001. “New Paradigms in Planning and Control across Manufacturing Supply Chains - The Utilisation of Internet Technologies.” *International Journal of Operations & Production Management* 21 (5/6): 582–593.

Kembro, Joakim, and Dag Näslund. 2014. “Information Sharing in Supply Chains, Myth or Reality? A Critical Analysis of Empirical Literature.” *International Journal of Physical Distribution & Logistics Management* 44 (3): 179–200. doi:http://dx.doi.org/10.1108/MRR-09-2015-0216.

Kembro, Joakim, and Kostas Selviaridis. 2015. “Exploring Information Sharing in the Extended Supply Chain: An Interdependence Perspective.” *Supply Chain Management* 20 (4): 455–470. doi:10.1108/SCM-07-2014-0252.

Kembro, Joakim, Kostas Selviaridis, and Dag Näslund. 2014. “Theoretical Perspectives on Information Sharing in Supply Chains: A Systematic Literature Review and Conceptual Framework.” *Supply Chain Management: An International Journal* 19 (5/6): 609–625. doi:10.1108/SCM-12-2013-0460.

Kiil, Kasper, Heidi C. Dreyer, Hans Henrik Hvolby, and Lukas Chabada. 2018. “Sustainable Food Supply Chains: The Impact of Automatic Replenishment in Grocery Stores.” *Production Planning and Control* 29 (2). Taylor & Francis: 106–116. doi:10.1080/09537287.2017.1384077.

Kiil, Kasper, Hans-Henrik Hvolby, Jacques Trienekens, Behzad Behdani, and Jan Ola Strandhagen. 2019. “From Information Sharing to Information Utilization in Food Supply Chains.” *International Journal of Information Systems and Supply Chain Management* 12 (3): 85–109.

Klein, Richard, and Arun Rai. 2009. “Interfirm Strategic Information Flows in Logistics Supply Chain Relationships.” *MIS Quarterly* 33 (4): 735–762. doi:10.2307/20650325.

Kovács, Gyöngyi, and Karen M. Spens. 2005. “Abductive Reasoning in Logistics Research.” *International Journal of Physical Distribution & Logistics Management* 35 (2): 132–144. doi:10.1108/09600030510590318.

Lee, Chang Hun, and Byoung Chun Ha. 2018. “The Impact of Buyer-Supplier Relationships’ Social Capital on Bi-Directional Information Sharing in the Supply Chain.” *Journal of Business and Industrial Marketing* 33 (3): 325–336. doi:10.1108/JBIM-01-2017-0021.

Li, Yina, Fei Ye, and Chwen Sheu. 2014. “Social Capital, Information Sharing and Performance: Evidence from China.” *International Journal of Operations & Production Management* 34 (11): 1440–1462.

Lusiantoro, L, N Yates, C Mena, and L Varga. 2018. *A Refined Framework of Information Sharing in Perishable Product Supply Chains*. *International Journal of Physical Distribution & Logistics Management Logistics Management*. Vol. 48. doi:10.1108/IJPDLM-08-2017-0250.

Man, C.M.D. 2016. “Food Storage Trials.” In *The Stability and Shelf Life of Food*, edited by Persis Subramaniam, 2nd ed., 171–198. Cambridge: Woodhead Publishing.

Marquès, Guillaume, Caroline Thierry, Jacques Lamothe, and Didier Gourc. 2010.

"A Review of Vendor Managed Inventory (VMI): From Concept to Processes." *Production Planning & Control* 21 (6): 547–561. doi:10.1080/09537287.2010.488937.

Mena, Carlos, Leon A. Terry, Adrian Williams, and Lisa M. Ellram. 2014. "Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector." *International Journal of Production Economics* 152. Elsevier: 144–158. doi:10.1016/j.ijpe.2014.03.012.

Meredith, J. 1998. "Building Operations Management Theory through Case and Field Research." *Journal of Operations Management* 16 (4): 441–454. doi:10.1016/S0272-6963(98)00023-0.

Moberg, Christopher R., Bob D. Cutler, Andrew Gross, and Thomas W. Speh. 2002. "Identifying Antecedents of Information Exchange within Supply Chains." *International Journal of Physical Distribution & Logistics Management* 32 (9): 755–770.

Mohr, Jakki, and John R. Nevin. 1990. "Communication Strategies in Marketing Channels: A Theoretical Perspective." *Journal of Marketing* 54 (4): 36–51. doi:10.2307/1251758.

Montoya-Torres, Jairo R., and Diego A. Ortiz-Vargas. 2014. "Collaboration and Information Sharing in Dyadic Supply Chains: A Literature Review over the Period 2000–2012." *Estudios Gerenciales* 30 (133). Universidad ICESI: 343–354. doi:10.1016/j.estger.2014.05.006.

Myrelid, Paulina, and Patrik Jonsson. 2019. "Determinants of Information Quality in Dyadic Supply Chain Relationships." *The International Journal of Logistics Management* 30 (1): 356–380.

Nakandala, Dilupa, Premaratne Samaranayake, and Henry Lau. 2017. "Modelling Information Flow and Sharing Matrix for Fresh Food Supply Chains." *Business Process Management Journal* 23 (1): 108–129. doi:10.1108/BPMJ-09-2015-0130.

Nielsen. 2018. *Western European FMCG Report Q4 2017*.

Olhager, Jan, and Martin Rudberg. 2002. "Linking Manufacturing Strategy Decisions on Process Choice with Manufacturing Planning and Control Systems." *International Journal of Production Research* 40 (10): 2335–2351. doi:10.1080/00207540210131842.

Pålsson, Henrik, and Ola Johansson. 2009. "Supply Chain Integration Obtained through Uniquely Labelled Goods: A Survey of Swedish Manufacturing Industries." *International Journal of Physical Distribution & Logistics Management* 39 (1): 28–46. doi:10.1108/09600030910929174.

Panahifar, Farhad, Cathal Heavey, PJ Byrne, and Hamed Fazlollahtabar. 2015. *A Framework for Collaborative Planning, Forecasting and Replenishment (CPFR). Journal of Enterprise Information Management*. Vol. 28. doi:10.1108/JEIM-09-2014-0092.

Paulraj, Antony, Augustine A. Lado, and Injazz J. Chen. 2008. "Inter-Organizational Communication as a Relational Competency: Antecedents and Performance Outcomes in Collaborative Buyer-Supplier Relationships." *Journal of Operations Management* 26 (1): 45–64.

doi:10.1016/j.jom.2007.04.001.

Pramatari, Katerina, and Panagiotis Miliotis. 2008. "The Impact of Collaborative Store Ordering on Shelf Availability." *Supply Chain Management: An International Journal* 13 (1): 49–61. doi:10.1108/13598540810850319.

Romsdal, Anita. 2014. *Differentiated Production Planning and Control in Food Supply Chains*.

Romsdal, Anita, Jan Ola Strandhagen, and Heidi Carin Dreyer. 2014. "Can Differentiated Production Planning and Control Enable Both Responsiveness and Efficiency in Food Production ?" *Int. J. Food System Dynamics*, no. April 2018: 34–43. doi:10.18461/ijfsd.v5i1.514.

Sheu, Chwen, HsiuJu Rebecca Yen, and Bongsug Chae. 2006. "Determinants of Supplier-Retailer Collaboration: Evidence from an International Study." *International Journal of Operations & Production Management* 26 (1): 24–49.

Siddh, Man Mohan, Gunjan Soni, and Rakesh Jain. 2015. "Perishable Food Supply Chain Quality (PFSCQ) - A Structured Review and Implications for Future Research." *Journal of Advances in Management Research* 12 (3): 292–313. doi:10.1108/02656710210415703.

Simatupang, Togar M., and Ramaswami Sridharan. 2005a. "The Collaboration Index: A Measure for Supply Chain Collaboration." *International Journal of Physical Distribution & Logistics Management* 35 (1): 44–62. doi:10.1108/IJBM-07-2013-0069.

Simatupang, Togar M., and Ramaswami Sridharan. 2005b. "An Integrative Framework for Supply Chain Collaboration." *The International Journal of Logistics Management* 16 (2): 257–274.

Småros, Johanna. 2007. "Forecasting Collaboration in the European Grocery Sector: Observations from a Case Study." *Journal of Operations Management* 25 (3): 702–716. doi:10.1016/j.jom.2006.06.005.

Spenhoff, Philipp, Marco Semini, Erlend Alfnes, and Jan Ola Strandhagen. 2014. "The Fit of Planning Methods for the Part Manufacturing Industry, a Case Study." *Advances in Manufacturing* 2 (2): 165–172. doi:10.1007/s40436-014-0075-0.

Tan, Keah Choon, Vijay R. Kannan, Chin-Chun Hsu, and G. Keong Leong. 2010. "Supply Chain Information and Relational Alignments: Mediators of EDI on Firm Performance." *International Journal of Physical Distribution & Logistics Management* 40 (5): 377–394.

Taylor, David H., and Andrew Fearne. 2009. "Demand Management in Fresh Food Value Chains: A Framework for Analysis and Improvement." *Supply Chain Management* 14 (5): 379–392. doi:10.1108/13598540910980297.

Thomé, Antonio Márcio Tavares, Roberto Luis Hollmann, and Luiz Felipe Roris Rodriguez Scavarda do Carmo. 2014. "Research Synthesis in Collaborative Planning Forecast and Replenishment." *Industrial Management & Data Systems* 114 (6): 949–965. doi:10.1108/IMDS-03-2014-0085.

van Donselaar, Karel H, Vishal Gaur, Tom Van Woensel, A C M Rob, Jan C Fransoo, Karel H Van Donselaar, Tom Van Woensel, Rob A C M Broekmeulen, and Tan C Fransoo. 2010. "Ordering Behavior in Retail Stores and Implications for

Automated Replenishment." *Management Science* 56 (5): 766–784.
Vanpoucke, Evelyne, Kenneth K. Boyer, and Ann Vereecke. 2009. "Supply Chain Information Flow Strategies: An Empirical Taxonomy." *International Journal of Operations & Production Management* 29 (12): 1213–1241.
VICS. 2004. *Collaborative Planning, Forecasting, and Replenishment. Collaborative Planning, Forecasting and Replenishment (CPFR®), An Overview*.
VICS. 2010. *Linking CPFR and S&OP : A Roadmap to Integrated Business Planning*.
Wänström, Carl, and Patrik Jonsson. 2006. "The Impact of Outsourcing on Materials Planning." *Journal of Manufacturing Technology Management* 17 (5): 561–584.
Watabaji, Mulugeta D., Adrienn Molnar, Robert D. Weaver, Manoj K. Dora, and Xavier Gellynck. 2016. "Information Sharing and Its Integrative Role: An Empirical Study of the Malt Barley Value Chain in Ethiopia." *British Food Journal* 118 (12): 3012–3029. doi:10.1108/BFJ-11-2015-0423.
Whipple, Judith M., and Dawn Russell. 2007. "Building Supply Chain Collaboration: A Typology of Collaborative Approaches." *The International Journal of Logistics Management* 18 (2): 174–196. doi:10.1108/09574090710816922.
Xu, Kefeng, Yan Dong, and Yu Xia. 2015. "'Too Little' or 'Too Late': The Timing of Supply Chain Demand Collaboration." *European Journal of Operational Research* 241 (2): 370–380. doi:10.1016/j.ejor.2014.09.006.
Yigitbasioglu, Ogan M. 2010. "Information Sharing with Key Suppliers: A Transaction Cost Theory Perspective." *International Journal of Physical Distribution & Logistics Management* 40 (7): 550–578.
Yin, Robert K. 2014. *Case Study Research: Design and Methods*. 5th ed. California: SAGE Publications Inc.
Yu, Wantao, Mark A. Jacobs, W. David Salisbury, and Harvey Enns. 2013. "The Effects of Supply Chain Integration on Customer Satisfaction and Financial Performance: An Organizational Learning Perspective." *International Journal of Production Economics* 146 (1). Elsevier: 346–358. doi:10.1016/j.ijpe.2013.07.023.
Zhou, Honggeng, and W. C. Benton. 2007. "Supply Chain Practice and Information Sharing." *Journal of Operations Management* 25 (6): 1348–1365. doi:10.1016/j.jom.2007.01.009

PAPER #3

Replenishment Planning of Fresh Meat Products: Case Study from a Danish Wholesaler

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Replenishment Planning of Fresh Meat Products: Case Study from a Danish Wholesaler

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Abstract. Replenishment planning of meat products with short shelf life is studied through a Danish wholesaler case-study. Main findings are that timeliness and frequency of information sharing adapted to demand dynamics can derive higher service level, and, that increased collaboration, regardless of integration, is important to obtain higher service levels. This study suggests uniform planning for both normal and campaign demand to enhance service level and profit for the normal demand.

Keywords: Collaboration · Integration · Replenishment planning · Fresh meat · Perishable

1. Introduction

Today, consumers have increasing power and requirements to the highly competitive grocery sector [1], demanding low price, at the same time with high availability, quality (i.e. freshness of products) and variety of products [2]. This has led to increasing collaboration across the supply chain, differentiated demand planning (campaign versus normal sale) [3] and emerging of replenishment programs [4], overcoming e.g. the lack of visibility of downstream sales, plans and inventory levels through distributing responsibility of planning according to competences and capabilities [5–10]. Albeit benefits of the collaborative programs (such as Efficient Consumer Response (ECR) and Collaborative Planning, Forecasting and Replenishment (CPFR)) are well documented, Mena et al. [11] find only few instances of these initiatives being used in practice.

Therefore, it is relevant to investigate how the replenishment is conducted in practice and what is the effect of it on the service level. The purpose of this study is to investigate if the differentiated planning approach as described in theory for different contexts (i.e. normal and campaign sale) applies for fresh meat products with shelf life less than 14 days. This is studied with one of Denmark's biggest wholesalers supplying the second largest and fastest growing discount retail chain in Denmark, which has not implemented a specific replenishment program. Moreover, the collaboration and information sharing (i.e. replenishment program) required to ensure downstream requirements for availability is studied. By comparing the wholesaler's approach against existing replenishment programs, it is possible to identify how collaboration and integration plays role on the replenishment performance. Focus is on meat products with shelf life up to 14 days. The following presents the theoretical background for collaboration, integration and structure of existing replenishment programs. Next, the methodology is presented followed by presentation of the case study, the analysis, discussion and conclusion.

2. Theoretical Framework

Replenishment programs can be categorized as either non-collaborative traditional replenishment (TR) or collaborative automated replenishment programs (ARP). Whereas TR is a one-time replenishment, ARP can be executed through different concepts like, efficient replenishment (ER), continuous replenishment program (CRP), vendor-managed and -owned inventory (VMI and VOI), collaborative buyer-managed forecasting (CBMF) and collaborative planning, forecasting and replenishment planning (CPFR). A literature study on TR and ARP programs is conducted and their main characteristics across a number of parameters are shown in Table 1. In general literature differs between the different replenishment programs through level of collaboration and integration with supply chain stages, and the (quantitative and/or qualitative) information shared [11, 12].

Table 1: Collaboration and Context Characteristics of Replenishment Programs

Parameters	TR	ER	CRP	VMI/ VOI	CBMF	CPFR
information sharing level (col)	very low	low	medium	mediu m	high	very high
information shared (col)	placed order	placed order	incoming order, sales forecast, inventory level, promotions, upcoming campaigns, performance metrics, delivery schedules…		… historical consumptio n patterns, market-product intelligence …	… long-term goals and plans
demand-input (col)	hist. order s	POS	POS	POS	POS	POS
developer of forecast (col)	W	W	W	S	W/S[1]	W & S
replenishment responsible (col)	W	W	W (/S[2])	S	S	W & S
order dispatcher (col)	W	W	W	S	S	S
collaborative planning (col)	no	no	(yes)[3]	no	yes	yes
planning time-horizon (col)	short	short	medium	short	medium	long
relationship-term (col)	short	medium	medium	long	long	long
demand pattern (con)	any	any	stable	stable	stable with exception	less stable[4]
product type (con)	all types	all types	all types	standar d	intro & seasonal	critical

Col = collaboration/con = context, W = wholesaler/S = supplier, [1]best capable, [2]different between authors, see e.g. Verheijen [13], Reyes & Bhutta [14], 3combined with ECR, [4]CPFR is more tolerant to instability than VMI.

The (external) integration is the configuration-oriented structuring and connection of processes and data to better facilitate the flow and availability of information, products and services between supply chain stages [15–17], hence how to share. The programs range from no integration, connecting through paper, call, fax or email (i.e. TR), to electronic data interchange (EDI) (i.e. ER, CRP and VMI/VOI) to internet-based integration (i.e. CBMF and CPFR). (External) collaboration is the relational and informational cooperation for working across organisational boundaries and sharing resources (information, people and technology) resulting in competitive advantage [15–17], hence what and how much to share. TR entails very low collaboration, low information sharing, and decentralized forecasting and inventory management. ARP enables collaborating supply chain stages, enhancing service provided to downstream stages, by sharing "information in advance and work together to develop realistic, informed and detailed estimates that can be used to guide business operations" [7]. Depending on the ARP program, information sharing is from merely placed order to extensive sharing of e.g. point-of-sales, inventory levels and strategies [5, 18], allowing replenishments based on actual sales, resulting in higher product availability at lower costs [4]. During time, ARP has moved towards more information sharing proportionally between supply chain stages with only

VMI/VOI deviating (greater buyer sharing) [5, 13]. The programs are either supplier (i.e. VMI/VOI), buyer (i.e. TR and ER) or equally dominated (i.e. CRP), or, distinct collaborative (i.e. CBMF and CPFR). The evolvement of programs have focused from single-transaction relationship (i.e. TR) to medium (<12 months) to long-term (>12 months) relationship. For planning, CPFR is long-term (>12 months), CRP and CBMF medium-term (6-12 months) and the remaining primarily short-term programs (<6 months). The programs relate to different contexts, e.g. VMI for standard products stable demand, CPFR for critical products with less stable demand (compared to VMI) and CBMF for introduction of and seasonal products with exceptions demand [9].

3. Methodology

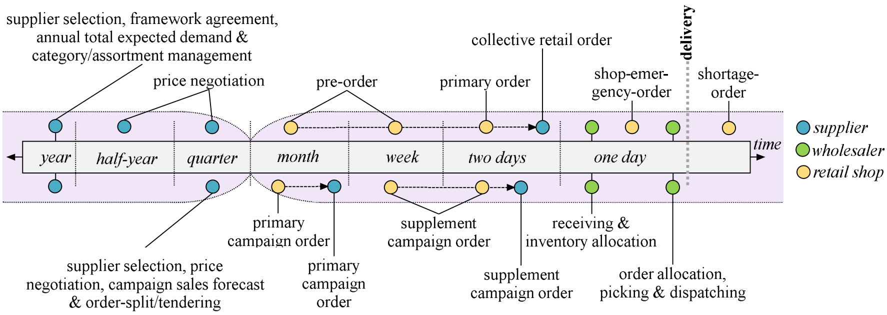
This study presents an empirical case-study research, following Flynn's six-stage framework for explorative case study [19], about fresh meat products' replenishment planning and the level of collaboration and information sharing to ensure downstream availability. Since both context and delivery performance are important in this case, studying the phenomenon in depth in natural context allows rich insight and good understanding of existing experiences [20, 21]. To provide a generalizable view of replenishment planning, focus is on four different types of meat products at on one of the biggest and fastest growing retail chains in Denmark and its 16 different first tier suppliers. Due to commercial confidentiality, the company is called ABC throughout this article, and, data is indexed per mean values or stated in percentage. To strengthen validity of the study, four types of meat products with short shelf life are in focus, beef, pork, chicken and fish. Information and data for understanding the different replenishment processes was gathered through semi-structured interviews with product manager and purchasers, evolving from standardized questions. Quantitative data for the whole year 2016 about ordered and delivered amounts has been extracted from the company's enterprise resource planning (ERP) system, for all shops on daily level per SKU with shelf life of two weeks or less. In total, 46,356 unique data points (ordered and delivered quantities) are identified, categorized as either normal or campaign sale, for meat type, with service level to shops as performance indicator.

4. Case Study

ABC is part of Scandinavia's biggest player within grocery and service trading. A centralized warehouse supplies the almost 300 discount shops in Denmark, receiving products either on Mondays, Wednesdays and Fridays (MWF-shops), or, Tuesdays, Thursdays and Saturdays (TTS-shops). ABC's overall goal is to be Scandinavia' most value-driven company and uses service level as primary performance indicator. In 2016, ABC supplied 201 different SKUs (53 beef, 45 chicken, 70 pork and 33 fish) from 16 suppliers (five for beef, two for chicken, seven for pork and two for fish). All products have the same lead-time from order dispatch to delivery, down to 36 hours.

For meat products, ABC uses a so-called “transit”-flow where products are ordered in exact amounts with no stock keeping, six days per week. The replenishment and planning cycles are presented in Figure 1 at a time continuum, where activities above the timeline are for assortment sale and below the timeline for campaign sale.

Figure 1: Time Continuum for Replenishment Planning Activities



For assortment products, shops send orders via computer or handheld order-terminal to ABC’s ERP-system via EDI at latest 18:00 two days before expected delivery. From 18:00 to 19:00, ABC sums up and aggregates all shop-orders into orders for each supplier. Shortly after 19:00, ABC sends orders to suppliers manually via mail or automatically via EDI (vast amount) depending on the supplier’s IT-system. For products on campaign, shops send a primary order four weeks in advance and ABC forwards these to supplier as totals similarly four weeks in advance. If a shop has orders too few or too many products on its primary order, it has the option of dispatching supplementing orders or reducing existing order, up until two days before delivery. The day after placing the orders, between 06:00 and 15:00 (down to 11 hours after order dispatch), the products arrive to ABC. After registering and reporting all incoming deliveries to the warehouse management system (WMS), information is transferred to the ERP-system. If a shop has not send an order the day before in due time, ABC may accept the order as an emergency order, depending on the reason (e.g. IT breakdown) and if the supplier can deliver the additional amount(s). In extreme cases, if supplier cannot deliver, ABC reduces other large shop-orders selectively by a few to accommodate the emergency order. Shop-orders are transferred from ERP-system to the WMS, ready for picking, from around 16:00. Received and delayed (same-day) incoming quantities are allocated to the individual shop-orders. Between 20:00 and 04:00 the next day, products are picked and packed, and dispatched from ABC to the shops from around 02:00 until around 07:00 in the morning.

ABC negotiates price for assortment products, with suppliers every three to six months. If there are several potential suppliers for a product, ABC may choose a different supplier with lower price, and, same or higher quality and delivery degree. For campaign-products, to assure competitive pricing, ABC sends demand forecast to suppliers via a tendering-like process, approximately three months prior to campaign start. Depending on price, quality and delivery degree, and if a single supplier can supply total expected demand, a single/several supplier(s) is/are chosen. If several, ABC splits the orders according to capacity available at each supplier. At annual meetings, typically in November and early December, ABC and suppliers agree upon a framework agreement (logistics terms, payment terms etc.), and ABC informs suppliers about total expected sales for upcoming year and category/assortment changes.

ABC has limited integration with suppliers (only EDI for some) and the collaboration is higher for campaign sale than for normal sale. Whereas ABC expects suppliers to supply normal demand without any further notice, ABC shares campaign demand forecasts and shop-orders, respectively three months and four weeks in advance. This, to notify the supplier about upcoming deviating demand behaviour, allowing him to plan and source raw materials accordingly. Interviews with procurement departments further highlighted that shops typically order 20-25% below actual demand when sending orders months in advance – but suppliers know this (from historical order data and behaviour) and adjust their internal plans accordingly.

ABC integrates with shops through EDI in order receiving, and does not collaborate any further when planning, leaving shops with individual responsibility in planning. If ordered too many products, shops may change the primary order up until normal deadline for order-dispatch (18:00 two days before delivery). However, changes allowed are smaller and smaller the closer to deadline. If supplementing orders exceed supplier' capacity, the available amount of raw materials to produce ordered product-quantities is split between the two upcoming deliveries to ABC (i.e. MWF- and TTS-shops), allowing all shops to receive products.

5. Analysis

5.1. Comparing Normal & Campaign Demand & Service Levels

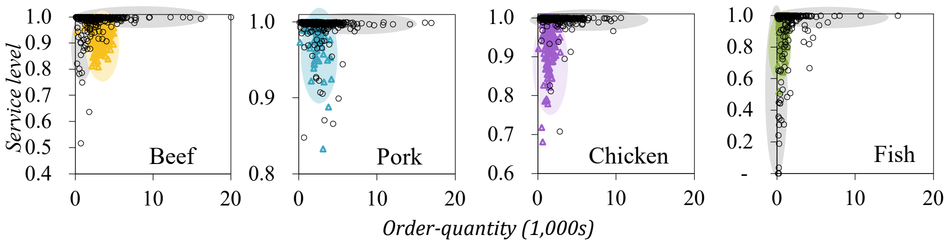
The quantitative investigation showed that ABC during 2016 faced a demand of more than 5.5 million boxes of meat products with shelf life less than 14 days (beef/pork/chicken/fish). Upper part of Table 2 provides statistical information about the demand throughout the year for each meat-type, where *N* is number of days with a demand (campaign or normal) during the year. Values are indexed against mean demand for each meat types' demand type (hence, all have a mean value of 100). For 50% of the observations (IQR), campaign demand deviates up to 3.7 times more across an up to 3.5 times broader range than normal demand. In terms of demand distributions' peaking behaviour (i.e. kurtosis), campaign demand is very leptokurtic, and normal demand is comparable almost mesokurtic (even platykurtic for fish) with a more flat and "random" demand pattern. Looking at skewness, campaign demand has a higher frequency of less-than-mean as opposed to normal demand's more symmetrical distribution with tendency of higher frequency of above-mean demand. Campaign demand is characterized by few large and many small campaigns, normal demand is characterised by few small and many large demand observations. Lower part of Table 2 summarizes service levels for product and demand types. The analysis showed a mean delivery degree for all meat products of 97.99%. The service level for campaign deliveries is characterized by being more negatively skewed and more frequently closer to 100% than for normal deliveries. Oppositely the demand behaviour, service level for normal deliveries fluctuates more and over broader range. Service level for 75% of campaign deliveries are above 99.2% (beef), 99.7% (pork and chicken) and 98.5% (fish) – all with leptokurtic distribution around 99.9% (beef, 99.8%). 75% of normal deliveries' service levels are 6.4% (beef), 0.5% (pork), 4.9% (chicken) and 2.6% (fish) lower than for campaign. Figure 2 illustrates campaign versus normal demand service levels (circles are campaign sale and triangles normal), showing that campaign deliveries, regardless order size, generally have higher service levels than normal, with only fish products having a more scattered relation.

Table 2: Group-Indexed Demand and Service Levels of Meat Products, Year 2016

Demand		***N***	**Mean ± SD**	**Median**	**IQR**	**Kurtosis**	**Skewness**
Beef	C	*310*	100±84.791	80.510	49.341-126.836	14.455	2.963
	N	*312*	100±24.567	103.159	82.346-116.596	0.354	-0.431
Pork	C	*309*	100±77.241	80.192	51.403-131.288	10.518	2.549
	N	*312*	100±21.049	100.141	88.452-111.334	3.215	-0.266
Chicken	C	*304*	100±65.339	89.945	48.961-128.301	2.859	1.433
	N	*312*	100±28.302	99.111	81.914-118.459	0.344	0.002
Fish	C	*297*	100±113.162	71.387	34.425-117.625	27.229	4.140
	N	*312*	100±40.590	106.716	66.212-133.564	-0.986	-0.198
Service level		**n**	**Mean ± SD**	**Median**	**IQR**	**Kurtosis**	**Skewness**
Beef	C	310	0.983±0.048	0.998	0.992-1.000	39.556	-5.531
	N	312	0.956±0.045	0.973	0.928-0.995	0.195	-1.004
Pork	C	309	0.994±0.019	0.999	0.997-1.000	29.189	-5.145
	N	312	0.992±0.017	0.998	0.992-0.999	31.859	-4.765
Chicken	C	304	0.994±0.024	0.999	0.997-1.000	80.260	-8.297
	N	312	0.966±0.050	0.990	0.948-0.999	6.578	-2.272
Fish	C	297	0.934±0.173	0.999	0.985-1.000	11.552	-3.356
	N	312	0.962±0.069	0.996	0.959-0.999	9.464	-2.819

C = campaign sales, N = normal sales

Figure 2: Campaign & Normal Service Levels versus Order Size for Meat Products



5.2. Replenishment Planning

ABC uses aspects from different replenishment programs, depending on whether the planning regards normal or campaign demand. ABC' approach for normal demand is similar to those of low collaboration (e.g. TR and ER). There is no distinctive collaboration and integration with suppliers, sharing only orders through mail or EDI and planning is individual, based on historical orders. For campaign demand, ABC' approach is more like those of higher collaboration (e.g. CBMF and CPFR) in that of close collaboration and sharing of forecasted demand, incoming orders, upcoming campaigns and medium to long-term plans – yet with no distinctive integration. Since ABC acts as facilitator for the shops by negotiating price, adjusting assortment to shops' requirements and balancing the converging-diverging product flow, ABC has no distinct decision-making in order dispatching and replenishment planning in shops. ABC merely aggregates and forwards incoming orders to suppliers. Based upon the differences in replenishment planning and performed service levels for respectively normal and campaign demand, it is desirable to share more information and collaborate closer for normal demand, to create higher service levels for normal demand.

6. Discussion & Conclusion

One of the main findings is that information sharing timeliness and frequency adapted to the demand dynamics can derive higher service level from supplier to ABC to the shops (given the transit flow), thus greater revenue. For ABC, simply sharing demand data in advance for all demand types may lead to (perfectly) 100% service levels, giving an estimated revenue growth of 2.6% (more than USD 2.75 million) plus additional increase due to the constant availability. The literature suggests that a company' performance is relatively influenced by level of collaboration, and further enhanced by the level of integration [17] due to the suggested information sharing frequencies. For TR and ARP programs, level of integration is relative to the level of collaboration (TR versus ER/CRP/VMI/ VOI versus CBMF/CPFR). This is justified by the appropriateness of the programs relative to the context, e.g. CPFR and CBMF for campaign sale. However, two interlinked factors evident in the case study suggest that only collaboration is important to obtain high service levels, regardless context, and that integration does not play any role. This can be explained by two interlinked factors. First factor is the three-stage supply chain (supplier, wholesaler and shops), opposite to ARP programs mainly two-stages. By including three stages, the wholesaler's consolidating function allows reducing the need for integration. Albeit the main-reason for integration is to increase efficiency by better facilitating the flow and availability of information, (particularly) when having several downstream entities, case study suggests that the consolidating role of wholesaler makes the need of integration less, since the downstream flow of information is combined and unified into one upstream flow. Second factor is wholesaler' role as a transit point, where products are not stored for longer time. Meat products are, due to the rapid degradation, moved through the supply chain fast and produced down to 36 hours before delivery, following the make-to-order principle, delaying the production decoupling point.

This research has focused on major common meat types in grocery business, and more research is needed for other types to establish the level of validity in using non-integrated and uniform planning. The meat types in focus are with constant demand throughout the year, and other meat types may be influenced by e.g. seasonality or only sold for a certain period during the year. Also, this research has focused on discount shops which are heavily influenced by low price, availability, large amounts sold during campaign and high frequency of campaigns. Additional research is needed for other store-types such as convenience stores and hypermarkets with different characteristics (e.g. different campaign frequency and/or price level).

References

1. Fernie, J., Sparks, L., McKinnon, A.C.: Retail Logistics in the UK: Past, Present and Future. Int. J. Retail Distrib. Manag. 38, 894–914 (2010).
2. Jacobsen, P.Ø., Bjerre, M.: Effekt & Effektivitet, Dansk Dagligvarehandel 2003-2013. Copenhagen Business School (2015).
3. Whipple, J.M., Russell, D.: Building Supply Chain Collaboration: a Typology of Collaborative Approaches. Int. J. Logist. Manag. 18, 174–196 (2007).
4. Stank, T.P., Daugherty, P.J., Autry, C.W.: Collaborative Planning: Supporting Automatic Replenishment Programs. Supply Chain Manag. An Int. J. 4, 75–85 (1999).
5. Derrouiche, R., Neubert, G., Bouras, A.: Supply Chain Management: a Framework to Characterize the Collaborative Strategies. Int. J. Comput. Integr. Manuf. 21, 426–439 (2008).
6. Kubde, R.A., Bansod, S. V.: Collaborative Planning Forecasting and Replenishment Initiatives: A State of Art. Asian J. Ind. Eng. 2, 89–104 (2010).
7. Sabath, R.E., Autry, C.W., Daugherty, P.J.: Automatic Replenishment Programs: the Impact of Organizational Structure. J. Bus. Logist. 22, 91–105 (2001).
8. Attaran, M., Attaran, S.: Collaborative Supply Chain Management: The most Promising Practice for Building Efficient and Sustainable Supply Chain. Bus. Process Manag. J. 13, 390–404 (2007).
9. Alftan, A., Kaipia, R., Loikkanen, L., Sepns, K.: Centralised Grocery Supply Chain Planning: Improved Exception Management. Int. J. Phys. Distrib. Logist.

Manag. 45, 237–259 (2015).
10. Mena, C., Terry, L.A., Williams, A., Ellram, L.: Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector. Int. J. Prod. Econ. 152, 144–158 (2014).
11. Chopra, S., Meindl, P.: Supply Chain Management: Strategy, Planning and Operation. Pearson, New Jersey (2010).
12. Lambert, D.M.: Supply Chain Management - Processes, Partnership, Performance. Supply Chain Management Institute, Sarasota (2008).
13. Verheijen, B.: Drivers for Supply Chain Collaboration in Practice. In: PhD-thesis: Vendor-Buyer Coordination in Supply Chains. pp. 9–42. Erasmus Research Institute of Management, Rotterdam (2010).
14. Reyes, P.M., Bhutta, K.: Efficient Consumer Response: Literature Review. Int. J. Integr. Supply Manag. 1, 346–386 (2005).
15. Natour, A., Gibson, P., Gibson, P.: Supply Chain Integration and Collaboration for Performance Improvement: an Agency Theory Approach. In: 9th ANZAM Operations, Supply Chain and Services Management Symposium. pp. 503–519. , Geelong (2011).
16. Moharana, H., Murty, J.S., Senapati, S.K., Khuntia, K.: Coordination, Collaboration and Integration for Supply Chain Management. Int. J. Intersci. Manag. Rev. 2, 46–50 (2012).
17. Kache, F., Seuring, S.: Linking Collaboration and Integration to Risk and Performance in Supply Chains via a Review of Literature Reviews. Supply Chain Manag. An Int. J. 19, 664–682 (2014).
18. Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E.: Supply Chain Integration. In: Designing & Managing the Supply Chain: Concepts, Strategies & Case Studies. pp. 119–143. McGraw-Hill, New York (2003).
19. Flynn, B.: Empirical Research Methods in Operations Management. J. Oper. Manag. 9, 250–284 (1990).
20. Yin, R.K.: Case Study Research: Design and Methods. SAGE Publications Inc, California (2014).
21. Eisenhardt, K.M.: Building Theories from Case Study Research. Acad. Manag. Rev. 14, 532–550 (1989).

PAPER #4

Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration

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Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration

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Abstract. As per the Industry 4.0 vision, it is well established that 'Enterprise Integration' by inter-organizational collaboration in a supply chain can achieve competitive advantage for all the parties. However, not much study is done on the tools at the manufacturer's end that enable the real-time information sharing in between the integrated enterprises. This paper explores the role of manufacturing information systems (beyond ERP layer) to define the scope/role of smart factories to enhance 'visibility' (supply chain visibility). The findings contributed to developing a hypothesis that manufacturing operations management (MOM) systems, especially manufacturing execution systems (MES) of smart factories at 'manufacturer' can provide critical product-centric data to the 'wholesaler', thus enhancing supply chain performance. This position paper gives insights into the 'real-time information sharing' in the fresh food supply chain, by presenting the perspectives of both manufacturer (with MOM systems) and the wholesaler (with needs on real-time production data regarding shipments). Furthermore, it provides a conceptual model illustrating the scope of smart factories towards the manufacturing digitalization. Analysis explored through case example of a Danish meat manufacturer to investigate how MES tool can aid 'planning'. In addition, the paper also sets the agenda for future research in this area.

Keywords: Real-time systems, Enterprise information systems (BIS), Digital supply chains, Industry 4.0, Position paper

1. Introduction

1.1. Manufacturing Enterprise Information Systems in Industry 4.0

Industry 4.0 vision supports information-centric manufacturing and guides the manufacturing companies to acquire higher levels of digital capabilities to effectively utilize the available data. It necessitates the operations to take place by integrating systems along the supply chain. The integration (inter-organizational) of IT systems will result in improved planning and execution of supply chain activities, enabled by real-time information sharing. According to MESA international, MOM systems will provide critical information within the extended supply chain and MES is an enterprise information systems (EIS) in smart factories that operates in the MOM level (Level 3 as per ISA 95). It works as a decision support system with an objective to achieve process improvement as well as to improve supplier management. This, because MES enables product visibility throughout the ordering, manufacturing and delivery process.

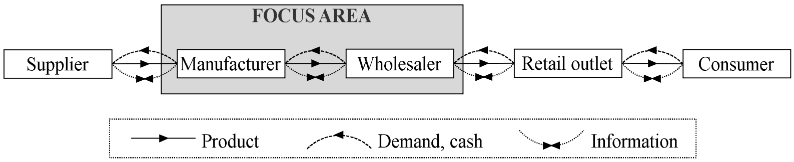
1.2. Fresh Food Supply Chains

Cyber-physical systems (CPS) in manufacturing environments (such as - production facilities, smart machines, storage systems etc.) of Industry 4.0, will be capable of autonomously exchanging information, also resulting in improved supply chains through smart factories. This is applicable to all the industries including the 'food industry'. Food supply chains are unique mainly due to the handling of 'perishable products'. The increasing consumer demand for constantly available fresh food products at a low price [1] [2], makes the management of the different flows across the supply chain (demand, product and information flows) extremely important, entailing effective decision-making and efficient flows. One predominant way of ensuring this is through information-sharing [3]. Due to the short shelf life of fresh food products, certain information should preferably be available and shared in the supply chain instantly when the disruptive phenomenon arises (i.e. in real-time). This allows the entire supply chain to react instantly upon the disruption rather than later.

Much research exists on the information sharing in different collaborative supply chain strategies. Information shared in supply chains include historical sales data, point-of-sales data, inventory levels, upcoming campaigns, promotions, performance metrics, company plans, incoming customer orders, market product intelligence etc. Despite this, there remains a need for investigating real-time information empirically as "real-time accessibility of specific information needs of entities" [4]. An interesting stream of information in relation to this is down-stream from manufacturer to wholesaler. During the execution-level in fresh food supply chains, real-time information can be a critical necessity in case of e.g. a production break-down at manufacturer stage.

This study focuses on information sharing between a meat-manufacturers and a wholesaler. It aims to put forward perspectives on the need for sharing information in real-time using MOM systems. The relation between the two case studies in focus is illustrated in fig.1 (see grey area), in the entire supply chain context. Products flow from supplier through the different supply chain stages to the consumer (i.e. downstream), with the demand and cash flowing from consumer towards supplier (i.e. upstream). In between each stage information normally flows both upstream and downstream. In this study, the information sharing is delimited to concern downstream from manufacturer to wholesaler.

Figure 1: Flows in between each stage



Section 2 describes the methodology and section 3 presents the outlook on real-time information sharing by presenting the perspectives. Section 4 discusses future research directions based on the preliminary iteration of the case study results, and concludes the position in section 4.

2. Methodology

This position study presents a selective literature review on MOM systems (of smart factories) in relation to real-time information sharing. The review results are used to explain how MES can enable visibility through real-time information sharing. Furthermore, core functionalities of MES that support this purpose were identified. The claims made based on the literature study were verified using an exploratory case study on one of Denmark's largest slaughterhouses (i.e. manufacturer) and the largest wholesaler. The case studies follow Flynn, et al. six-stage framework for conducting empirical research [5] about information systems support from manufacturer to wholesaler. Since the context and perspectives on real-time information systems are important to this study, an in depth study of the phenomenon in its natural context allowed good use of existing experiences [6] [7]. This allowed the study to reconcile evidence from observations and data with research literature. The cases contributed to empirically studying the needs of both the parties as well as their existing information systems.

First, a selective literature survey was conducted through 'google scholar' (database) with focus on latest research findings from the year 2010 - 2018. The key-words used in searching for papers are: 'enterprise information systems', 'MOM systems', 'smart factories', 'enterprise integration', 'traceability' 'supply chain visibility' 'manufacturing information', 'real-time information sharing'. This, to gain conceptual understanding on the manufacturing information systems support for integrated enterprises. A fresh food supply chain problem was considered due to the criticality of information relative to the short shelf life of some food products.

Second, two case companies were chosen within the fresh food industry. Due to commercial confidentiality, the manufacturer is called ‘Company-A’ and the wholesaler ‘Company-B’ throughout this article. Studying the secondary case company (company B) apart from the primary case company (company A), gave better understanding of the phenomenon.

- Company-A is one of the largest slaughterhouse in Denmark, handling pork and beef products. A centralized production facility in XXXX produces products to majority of the Danish meat market, including wholesalers, retailers, catering etc. Company-A’s goal is to be a knowledge driven enterprise by making the best use of technology and information to deliver best services.

- Company-B is one of the Scandinavia’s largest players within grocery and service trading, and is the largest grocery wholesaler in Denmark. Company-B supplies fresh meat products to more than 300 different grocery shops. Company-B’s overall goal is to be known as the most value-driven company in Scandinavia, with deep focus on ensuring high quality (i.e. fresh) products constantly (i.e. minimal supply disruption).

Information and data about current information sharing and perspectives on real-time information sharing was gathered through semi-structured interviews with manufacturing IT-architect (from company-A) and product manager (from company-B). The duration of the interview with company-A was around 150 minutes, which was electronically recorded and transcribed. The collected information was analyzed and coded into various categories. The category of smart factories for ‘demand and supply chain planning’ is picked as a problem area to empirically study how manufacturing information sharing via external collaboration (enterprise integration) can improve supply chain performance.

3. Findings – Outlook and Position

3.1. Status Quo

3.1.1. Enterprise Integration and Visibility in Supply Chains:

‘Connected enterprises’ is the term used to explain the digitally connected independent enterprises across the supply chains. The term also refers to e-business and information supply chains; all requiring real-time data sharing by connecting their information system elements [8]. Such a connected manufacturing enterprise is achieved by ‘enterprise integration’ where the information flow is made possible.

Operation visibility: With the enhanced digital capabilities of manufacturing enterprises, manufacturing operations can be planned, executed and controlled easily than before by enhancing traceability (being the ability to trace the history of all resources in the production process). On the other hand, to better the manufacturing processes, Industry 4.0 model is expected to fulfill the growing customer demands for faster real-time response by decentralized production control using MES to improve performance, quality and agility for globalized manufacturing businesses [9].

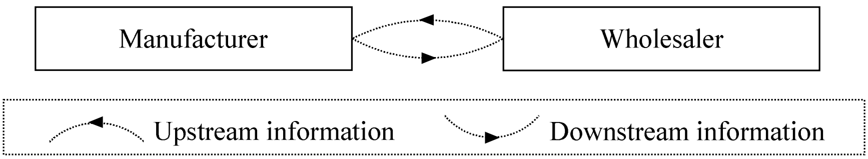
3.1.2. External Collaboration:

Information between the manufacturer and the wholesaler in supply chains is traditionally exchanged via bidirectional flows through EDI, fax, mail, internet and/or cloud. This exchange allows for attaching each supply chain stage together in relative degree [10], with information sharing considered a main part of collaboration.

“Rather than trying to independently project demand patterns, buyers and sellers share information in advance and work together to develop realistic, informed and detailed estimates that can be used to guide business operations” [11]. The level to which this is performed ultimately influences the supply chain success [12]. Hence, in the external collaboration context, sharing of information represents the exchange of any qualitative or quantitative data between any given supply chain stage and either downstream or upstream parties – i.e. manufacturer and wholesaler.

The below figure shows the inter-organizational (i.e. external) collaboration in the supply chain, between manufacturer and wholesaler (see fig. 2).

Figure 2: Information flows in between Manufacturer and Wholesaler



3.2. Perspective on Real-Time Information

3.2.1. Wholesaler Receiving Information:

‘Perishable products’ deteriorate in quality through time, with limited shelf life down to few days (e.g. grounded beef and sushi). These products have requirements to handling and storage to reduce the speed of deterioration [13]. If not handled and/or stored properly, these products may deteriorate faster and to a level making the products dangerous for human consumption. In spite of the existing demand and supply chain planning models’ (such as collaborative planning, forecasting and replenishment), the extent to which real-time data is actively used and reflected, still remains undiscovered for food distributors and retailers. This situation raises a need for reliable and constantly updated data, allowing all business functions to take decisions.

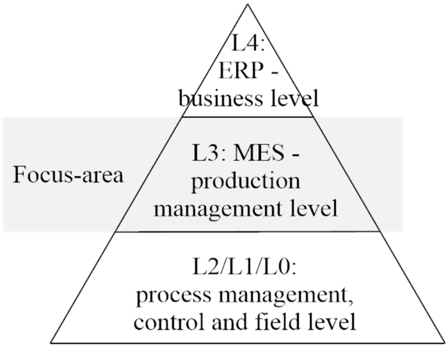
Further, product-centric data accessed by wholesaler through real-time systems, ensures constantly updated information about the products for the different supply chain parties. As example, for the wholesaler, real-time information from upstream stages (i.e. Manufacturer) about production break-down and possible scarcity in pending deliveries will allow the wholesaler to e.g. either try to source the products elsewhere in due time to minimize the impact on the customer (in the end, the consumer) – or distribute the available amounts across customers to ensure either supply to all customers or prioritized supply to customers. Today, information about over/under-supply in pending deliveries is typically exchanged through advanced shipping notifications (ANS), where the manufacturer informs about pending quantities to arrive at wholesaler. However, certain challenges exist in that the ANSs are sent when orders are dispatched, and not when the disruption arise – which may be several hours in advance. Hence, there is interest in applying diversified real-time data (on product and production information) for effective planning.

3.2.2. Manufacturer Providing Information:

Visibility through Smart factories: 'Information transparency' is one of the Industry 4.0 design principles as suggested by Hermann et al. [14]. As per the Acatech's vision for Industry 4.0, smart factories should have the ability to exchange information in real-time from one enterprise to another. Horizontal integration (as per production, Industrial automation and IT fields) is a strategy of integration of IT systems (also between different companies) to deliver an end-to-end solution [15].

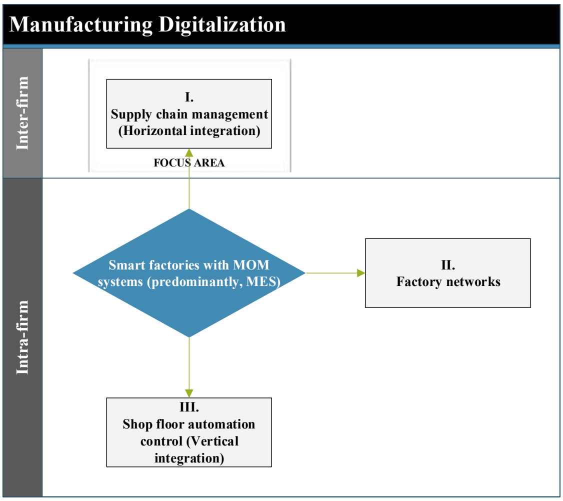
MES of MOM systems is identified to serve visibility through smart factories, considering its functionalities and access to manufacturing information of the product from the shop floor. Robust manufacturing EIS like MES are believed to support the process by providing product-centric information. MES is an industrial software that has undergone gradual developments with the advancements that occurred in the computing technologies and integration levels. Next generation MES comes with an extended scope to provide 'all-round view' of all the resources involved in the production and can be described as a 'manufacturing cockpit'[16]. The tool has now evolved to provide faster real-time responses to match the customer demands [17]. MES is better equipped to provide the manufacturing information to any other enterprise in the supply chain, in case of a requirement. Such a detailed manufacturing information in real-time is only available with MES but not with 'Enterprise resource planning' (ERP) tools that operates in the business management level (as per figure 3). SCADA of Level 2 is confined to the controlling of the equipment movement, whereas MES can control the overall production activity. Hence, SCADA systems can only track equipment level information but MES can track the production process information.

Figure 3: ISA 95 Levels of functional hierarchy in a manufacturing enterprise [18]



Below figure is designed in this paper to map the scope of visibility achieved through smart factories that use MOM systems:

Figure 4: Scope of Smart factory - Visibility of end-to-end information in Industry 4.0 model



Enterprises are required to look beyond their internal processes by extending their information systems to integrate with the partners of the supply chain. Even though linking ERP systems of different enterprises to achieve the inter-organizational information exchange is a popular method, ERP might not be able to provide an in-depth real-time information of the product to support the 'planning' issue in the supply chain. Most ERP systems operate on historical data in the inter-organizational integration setups and the existing enterprise integration solutions have difficulty in addressing this issue.

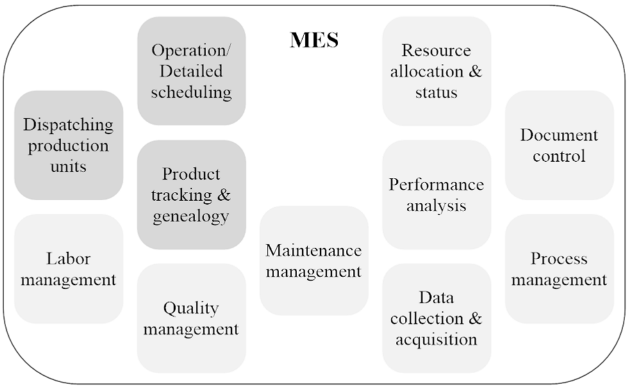
Product level information at the manufacturer end is captured by the Level 3 systems (level as per the ISA 95/IEC 62264 standard) of MOM layer of the shop-floor. MOM is predominantly supported by the MES, whose scope extends to scheduling and product delivery. Below are the 11 functionalities of MES, as per MESA International. In this paper, 3 functionalities of the 11 are identified to have links to supply chain management:

i) Operations/ Detailed scheduling

ii) Dispatching production units (real-time dispatch information on the factory floor tracked and flows are managed as jobs, orders, batches, lots and work orders)

iii) Product tracking and genealogy (on line visibility of the product status – component materials by suppliers, live production conditions, rework etc.)

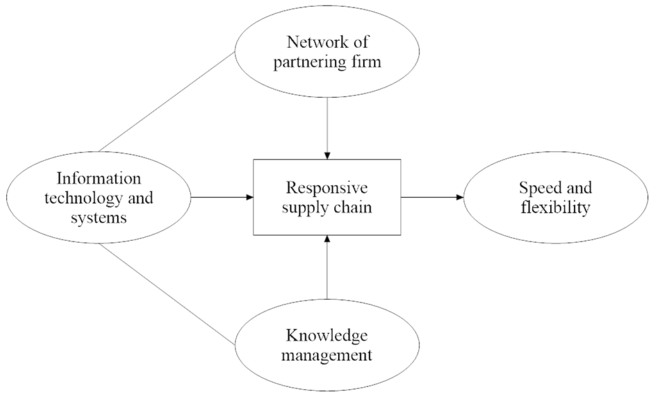
Figure 5: 11 functionalities of MES according to MESA International



The above mentioned feature of live tracking of the production conditions and exchange is not available at the enterprise level with ERP systems, in contrast to MES. Hence, MES is more equipped to provide the real-time information on the product to the wholesaler (to aid planning). Moreover, MES also promotes 'collaborative manufacturing' better than ERP, as it can provide traceability on the unit level and has an ability to give live production status reporting. "Collaborative manufacturing is to automate, link, complement, or support business processes across departmental, plant, enterprise, or supply chain boundaries [19]".

Software systems are the enablers of responsive supply chains (see fig. 6) and this model is supported through smart manufacturing using MOM systems like MES.

Figure 6: A responsive supply chain framework (Gunasekaran et al. [20])



With an objective to achieve supply chains that are flexible and responsive, MES is believed to provide real-time product-centric information to help the planning of wholesaler in collaborative manufacturing, achieved through inter organizational integration.

3.3. Claims

The qualitative analysis of literature as well as the case study of manufacturer and wholesaler helps in deducing that:

- Interdependencies on exchange of real-time manufacturing information exist as per the above two perspectives
- Defining the needs of the wholesaler is an important step to know what kind of information is to be provided by the manufacturer using MES, which results in collaborative manufacturing achieved through smart factories
- Providing real-time information on 'machine downtime' and 'failures on behalf of suppliers' is interesting for a manufacturer to meet the customer demands (customer of the manufacturer being wholesaler) and to simplify the methods of communication
- Receiving real-time manufacturing information is interesting for a wholesaler to react faster to any disruptions in supply from the manufacturer

The first iteration of the case study results are discussed in the following section 4, below. The preliminary analysis of the case study findings contributed to empirical verification of the theoretical propositions (based on the selective literature review) of section 3.2 and to further deduce the claims in section 3.3.

4. Results and Discussion

This study was done with an expectation to explore how smart factories can effectively exchange real-time information using MOM systems. It gave an understanding on the interdependencies of the enterprises and the purpose of having enterprise integration in the industry 4.0 context. Furthermore, it gave insights on how MES can act as a real-time system to enable such connectedness by providing information on flow of materials and manufacturing cycle times.

Practical Issues Surrounding the Vision: From the preliminary qualitative analysis of the interview of Company-A, it is understood that there is skepticism in having real-time systems such as cloud based MOM systems. This, due to the fear that manufacturer might face operating performance issues if the production stands still, in the case of a technical problem on cloud.

Challenges of Real-time Information Sharing: Real-time data sharing is easier with cloud-based MOM solutions. But, companies are interested in weighing the achievements of having cloud-based solutions against having a server onsite. More over systems integration of different enterprises also arises doubts on trust and security of data.

Future Research Directions: The expanded version of this paper requires an in depth analysis (second iteration) of the qualitative interview of Company-A with a problem based learning (PBL) approach. Problem being the supply chain planning and learning is expected to be achieved on MES (and other MOM software) as real-time systems. This to evaluate its functionalities that aid enterprise integration and visibility. The future work intends to evaluate the effectiveness of the proposed collaboration and integration using MES on the real-life industrial case of Company-A and Company-B to verify initial empirical findings by conducting second round of interviews for a qualitative synthesis. A future explanatory study that is empirical in nature could answer how 'real-time information sharing' (including upstreaming) is achieved through MES to resolve risks caused due to the issues of coordinating supply and demand in the supply chains.

5. Conclusion

This position paper is written based on the existing literature study on the concepts, along with preliminary (qualitative) analysis of a case example. The position taken helps in concluding that –

- There is a need for exchanging real-time information between supply chain parties because it is vital for realizing the concept of 'enterprise integration' for Industry 4.0
- To contribute to the field of manufacturing information systems, it is essential to investigate the need to use real-time systems like MOM systems/ MES (beyond ERP)
- MOM systems are central to smart factories for 'visibility' and their scope is presented through a conceptual model in the fig. 4
- MOM systems (predominantly MES) can provide real-time product data to the wholesaler, resulting in the improvement of supply chain performance

For theoreticians, this exploratory research paper gives insights into MES/MOM as real-time systems and enabling technologies for supply chain transformation. Future research directions could include trying to understand the benefits of MES across different industries, how the use of real-time information sharing through MES impacts total supply chain performance, as well as how real-time information sharing can be applied specifically to the three functionalities of MES described in this study.

For practitioners, the perspectives on manufacturing information sharing of 'manufacturer' to 'wholesaler' in the context on Industry 4.0 are presented. Research findings guide the design of factories of the future by prioritizing 'external collaboration' for digital supply chains to have productivity improvement in the business operations.

References

[1] P. Ø. Jacobsen and M. Bjerre, Effekt & Effektivitet, Dansk Dagligvarehandel 2003-2013. Copenhagen Business School, 2015.
[2] M. Munkøe and K. Beierholm, "Dansk Erhvervs Konjunkturanalyse for Detailhandlen, Februar 2015," Dansk Erhv., pp. 1–4, 2015.
[3] M. E. Ferguson and M. E. Ketzenberg, "Information Sharing to Improve Retail Product Freshness of Perishables," Prod. Oper. Manag., vol. 15, no. 1, pp. 57–73, 2006.
[4] D. Nakandala, P. Samaranayake, and H. Lau, "Modelling information flow and sharing matrix for fresh food supply chains," 2017.
[5] B. B. Flynn, S. Sakakibara, R. G. Schroeder, K. A. Bates, and E. J. Flynn, "Empirical Research Methods in Operations Management," J. Oper. Manag., vol. 9, no. 2, pp. 250–284, 1990.
[6] K. M. Eisenhardt, "Building Theories from Case Study Research," Acad. Manag. Rev., vol. 14, no. 4, pp. 532–550, 1989.
[7] R. K. Yin, Case Study Research: Design and Methods, 5th ed. California: SAGE Publications Inc, 2014.

[8] D. M. Levermore, G. Babin, and Cheng Hsu, “A New Design for Open and Scalable Collaboration of Independent Databases in Digitally Connected Enterprises,” J. Assoc. Inf. Syst., vol. 11, no. 7, pp. 367–393, 2010.
[9] F. Almada-Lobo, “The Industry 4.0 revolution and the future of Manufacturing Execution Systems (MES),” J. Innov. Manag., vol. 3, no. 4, p. 17, 2016.
[10] D. M. Lambert, Supply Chain Management - Processes, Partnership, Performance. Sarasota: Supply Chain Management Institute, 2008.
[11] T. P. Stank, P. J. Daugherty, and C. W. Autry, “Collaborative Planning: Supporting Automatic Replenishment Programs,” Supply Chain Manag. An Int. J., vol. 4, no. 2, pp. 75–85, 1999.
[12] S. Chopra and P. Meindl, Supply Chain Management: Strategy, Planning and Operation. New Jersey: Pearson, 2010.
[13] J. Evans, “Effects of Food and Beverage Storage, Distribution, Display, and Consumer Handling on Shelf Life,” in The Stability and Shelf Life of Food, 2nd ed., P. Subramaniam, Ed. Cambridge: Woodhead Publishing, 2016, pp. 107–140.
[14] M. Hermann, T. Pentek, and B. Otto, “Design principles for industrie 4.0 scenarios,” Proc. Annu. Hawaii Int. Conf. Syst. Sci., vol. 2016–March, pp. 3928–3937, 2016.
[15] H. (Deutsche P. A. Henning, Kagermann(National Academy of Science and Engineering). Wolfgang, Wahlster (German Research Center for Artificial Intelligence). Johannes, “Recommendations for implementing the strategic initiative INDUSTRIE 4.0,” Final Rep. Ind. 4.0 WG, no. April, p. 82, 2013.
[16] J. Kletti, Manufacturing Execution Systems – MES. Springer Berlin Heidelberg New York, 2007.
[17] R. G. Qiu and M. Zhou, “Mighty MESs; State-of-the-Art and Future Manufacturing Execution Systems,” IEEE Robot. Autom. Mag., vol. 11, no. 1, pp. 19–40, 2004.
[18] B. Scholten, The Road to Integration. ISA, 2007.
[19] M. Mcclellan, Collaborative manufacturing. 2003.
[20] A. Gunasekaran, K. hung Lai, and T. C. Edwin Cheng, “Responsive supply chain: A competitive strategy in a networked economy,” Omega, vol. 36, no. 4, pp. 549–564, 2008.

PAPER #5

Horizontal Integration in Fresh Food Supply Chain

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Role of PhD-candidate and declaration of authorship:
The PhD student defined the problem and proposed the structure and core scientific idea to solve it, together with second author (PhD student Soujanya Mantravadi). The PhD student derived key-methodology, conducted case-study research and interviews, collected and analysed data, wrote the entire draft version of the paper and revised it together with the second author, according to comments from other co-authors.

Horizontal Integration in Fresh Food Supply Chain

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Abstract. Demand information sharing during planning and control of fresh meat production and replenishment in franchise supply chain is studied. Main findings are that some demand information is received much later upstream than when created downstream. Horizontal integration of systems in the supply chain allows all parties access to same critical information about store demand and availability in real-time. A conceptual model for horizontal integration in the triadic supply chain, allowing differentiated and timely sharing of information is suggested, to increase service level and reduce waste from over-/under-production.

Keywords: Retail supply chain · Integration · Real-time information sharing · Fresh food products · MES

1. Introduction

In retail supply chains, information sharing [1, 2] is a large part of collaborative materials management (CMM) [3]. Sharing e.g. demand information allows transparency and visibility of product sales and availability in the supply chain. However, demand information is usually adjusted and aggregated downstream into orders before being shared, and is sent in batches at specified times or when manually initiating a transfer (e.g. sending purchase orders). It is often shared in dyadic structures via business level systems alike enterprise resource planning systems (ERP). Hence, supplier, wholesaler and retail stores plan (and schedule) and control their productions independently – based on (adjusted) historical rather than real-time information and internal plans cf. internal setup [4, 5]. Once scheduled, the production is frozen certain time into the future to reduce nervousness [4]. Albeit incremental planning is possible, options for changes continuously decrease, until finally impossible when production ends [4].

This is challenging when dealing with fresh food products. They need intensified and increased information sharing [6] during planning and control of production and replenishments, due to high demand variability and short shelf life [7]. Fresh meat products (FMPs) such as e.g. ground beef/pork/chicken/fish and ready-made meals are processed down to few hours before shipment to wholesaler; even while stores still send orders to wholesaler. Thus, sharing demand information longer time in advance of production start both increases demand uncertainty (cf.forecast) and reduces the supply chain responsiveness to unforeseen changes in demand. Even if possible, responses are costly and labor-intensive non-systemized exceptions management (through phone calls and emails). Instead, sharing centrally managed demand information [8] in real-time allows common understanding of demand, effective instant decision-making, reduced risks and greater forecast accuracy [9]. To not put more pressure on business level systems, interest is in horizontal integration of planning and control systems online/in the sky to share real-time. In addition, for franchise, all decision-making is decentralized to stores, as opposed to corporate retail chains. It is thus relevant to also investigate how a triadic supply chain (supplier, wholesaler and retail stores) seamlessly can share real-time demand information horizontally during planning and control.

We analyze and identify issues in information sharing during fresh meat production and replenishment planning and control in franchise retail supply chain. A conceptual model is proposed to integrate systems in the supply chain with real-time demand information sharing along suggestions for which information to share. Following presents theoretical framework, methodology, case analysis, framework and conclusion.

2. Theoretical Background

Collaborative materials management (CMM) is “operational planning and control of inventory replenishments in supply chains” [3]. Information sharing is a major part of CMM and governs the “capturing and dissemination of timely and relevant information for decision makers to plan and control supply chain operations” [2]. Especially demand information sharing influences CMM with direct impact on the planning and control effectiveness and waste from out-of-stock/oversupply situations [10–12].

In CMM there is differently increasing demand information sharing depending on the level of collaboration [8, 13, 14]. As example, in “vendor-managed inventory” (VMI) supplier may obtain full view of both historical demand, point-of-sales and inventory levels at wholesaler or retail stores (depending on whose inventory is managed). However, it only covers a dyadic supply chain limiting the efficient information sharing across entire (i.e. triadic) supply chain. Further, demand information sharing is through batch transactions from ERP or online access to ERP [13], causing redundant use of and pressure on ERP systems compared to if sharing directly between the systems where the information is created. The “collaborative planning, forecasting and replenishment” (CPFR) (VICS, 2014) includes demand exceptions and extends VMI with collaborative validation and synchronization of planning (incl. forecasting) by increasing demand information sharing. Yet, although information sharing is through special data transfer interfaces (e.g. EDI) [15] or even online applications for real-time/near real-time [16], it is still through ERP in a dyadic supplier-wholesaler relationship. Similarly for “process of collaborative store ordering” – although information sharing is through an online platform to enhance real-time demand sharing [14] it is dyadic between supplier and retail stores, i.e. without wholesaler’ knowledge to and about demand information [8]. No CMM program entails real-time based triadic demand information sharing via planning and control systems to ensure complete (supply chain) demand visibility and efficient use of systems. Namely for supplier’ manufacturing execution systems, wholesaler’ warehouse management system and retail stores’ cash register. For fresh food products with short shelf life there is stronger correlation between supply chain performance and level of information sharing, than long shelf life products [6]. Yet, although information sharing generally improves supply chain performance [17], responsiveness [18] and freshness of products [7], research also suggest that the level of improvement is not per se always positive as sharing too much/irrelevant information may decrease performance and “result in an expected loss” [19]. In turn, information sharing (and thus also collaboration) depends on factors such as e.g. specific demand situation [12, 20], type of product [6] as well as type of information shared, with whom it is shared and how it is shared [21].

From the production perspective, the concept of inter-enterprise integration and the supplier’s involvement in the supply chain using information systems is not new. Level 3 systems as per ISA 95 standard set by ‘International society of automation’ also address the need for systems to interconnect, to provide value to the manufacturing enterprises and beyond. Enterprise systems are known to enhance the collaboration between the supplier and the end user by reducing transaction costs [22]. Since MES/MOM systems are real-time compliant, it becomes advantageous for fresh food supply chains to access the product centric data via factory control systems [23]. Supplier can thus play an important role in improving the supply network design as problems related to bullwhip tend to impact all chain parties.

There are various approaches to interenterprise integration based on the need for information sharing. Owing to that, information exchange via web based MES/MOM systems can follow several classes of information interfaces such as: SCOR, CPFR, RosettaNet for process data; EDIFACT for structured data; and TCP/IP reference model & basic internet services for unstructured data [24]. Supplier and buyer integration in a supply chain for collaborative materials planning is a known method in the operations management. But the collaborative approach by integrating shop floor level systems is not well understood in theory. Over the last two decades, ERP systems have evolved from being monolithic to modular ERP II systems by extending into the supply chains [25]. Similarly, the scope of MES/MOM systems could also be extended into supply chains, for which we present web-based service-oriented architecture (SOA) as a suitable approach for horizontal integration. Modularity and remote access via internet technology are key reasons for considering service-oriented MES/MOM systems.

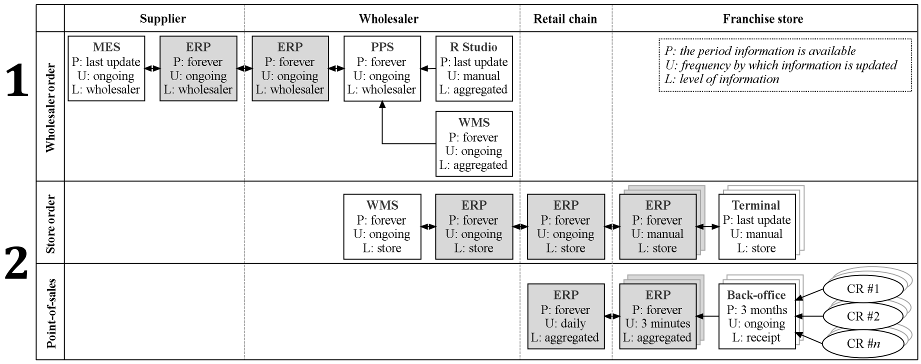
3. Methodology

After investigating demand information sharing in the supply chain and where different demand information is created, the purpose is to propose a conceptual model for real-time sharing through horizontal integration of planning and control systems. This, to ensure all parties access to same critical information about store demand and availability in real-time. The focus is on FMPs and ensuring decentralized order decision-making cf. franchise retailing. The goal is to ensure complete transparency of demand (i.e. store sales) and inventories across the supply chain in real-time, allowing live production scheduling at supplier. The case is studied in natural context to ensure enriched understanding and insight [26] as both context and product type is critical. To provide a generalizable view, focus is on beef, pork, chicken and fish with total shelf life of 8 days or less which are produced short time before delivery to wholesaler. The supply chain is triadic, i.e. supplier, wholesaler and retail stores (franchisors) with retail chain (franchisee). Wholesaler is one of the largest grocery wholesalers in Denmark and supplies 328 franchise stores with FMPs from five suppliers each day through a central warehouse, via two replenishment cycles: supplier-wholesaler and wholesaler-store. The past year stores have ordered 10 to 47 SKUs each day; 4-25 beef incl. veal and cattle, 1-16 pork, 1-9 chicken and 1-4 fish; depending on season/campaigns. All FMPs are shipped from supplier, consolidated at wholesaler and delivered to stores. Waste levels in stores from theft and expiration are considered very low (<1%, estimated) but included in the calculation of inventory levels. Information and data are obtained via semi-structured interviews with IT-manager, purchaser and purchasing manager (wholesaler), purchasing assistant (retail chain), personnel (retail stores) and, sales manager, production planner and vice president (supplier), from standardized questions about planning/scheduling/control processes.

4. Information Sharing in Fresh Meat Supply Chain

First, wholesaler creates an order in the purchase planning system (PPS) and sends it to supplier via ERP by latest 16:00 (day 1). After confirmation (via ERP), supplier schedules the order for production during the night/following morning and deliver to wholesaler between 06:00 and 13:00 (day 2). While the production still runs (supplier) and FMPs are received (wholesaler), stores create orders in their ERP via hand-terminals and send to retail chains' ERP at latest by 11:00 (day 2). The store orders are then transferred to wholesaler' ERP and further to the warehouse management system (WMS), releasing orders for picking from 14:00 in two batches (dependent on delivery times to stores). The FMPs are physically delivered to the stores between 18:00 (day 2) and 05:00 (day 3). This results in a lead-time of down to 14 hours for wholesaler, and down to 7 hours for stores, from sending store order until received. Figure 1 depicts where the demand information is created and available, grouped vertically by supply chain stage and type of demand information (see 1/2/3 in figure). White boxes, except “R Studio” (forecasting), are real-time information systems and the grey are ERP.

Figure 1: Order-information creation and storing in systems



Creation of Wholesaler Orders (1) and Transfer to Supplier (Cycle 1). Wholesaler forecasts total store demand (via R Studio) at daily level considering weekday-patterns. Based on this, inventory levels (from WMS) and yesterday’ store demand (from ERP), wholesaler estimates the following day’ demand. Although (aggregated) POS from yesterday’ sale in stores can be accessed, is not used since logging on retail chain’ ERP and looking up each product’ sale in stores is rather time-consuming. When order quantity is set (i.e. expected demand minus incoming pre-orders and inventory), the order is loaded into wholesaler’ ERP. The purchaser manually sends the order to the supplier through EDI-FACT, awaiting an order confirmation. In Figure 1, from right to left.

Creation of Store Orders (2) and Transfer to Wholesaler (Cycle 2). When stores order products, personnel walk around in the store and scan shelf labels with a handheld terminal as seem needed, i.e. less available than desired. The personnel can see usual sales the given weekday (manually uploaded to the terminal from ERP before starting the ordering process). Quantity is determined from what pre-determined amount to be available minus actual available amount in boxes – and adjusted for sales the following day if it is expected to increase. When the order is final, it is transferred from to the ERP. For each product, the personnel see what is usually sold at surrounding days, general historical sale, campaign information (last/current) and how much is in pre-order. When adjusted the order is sent to retail chain’ ERP, and then to wholesaler' ERP and from here further to the WMS for picking. In Figure 1, from right to left.

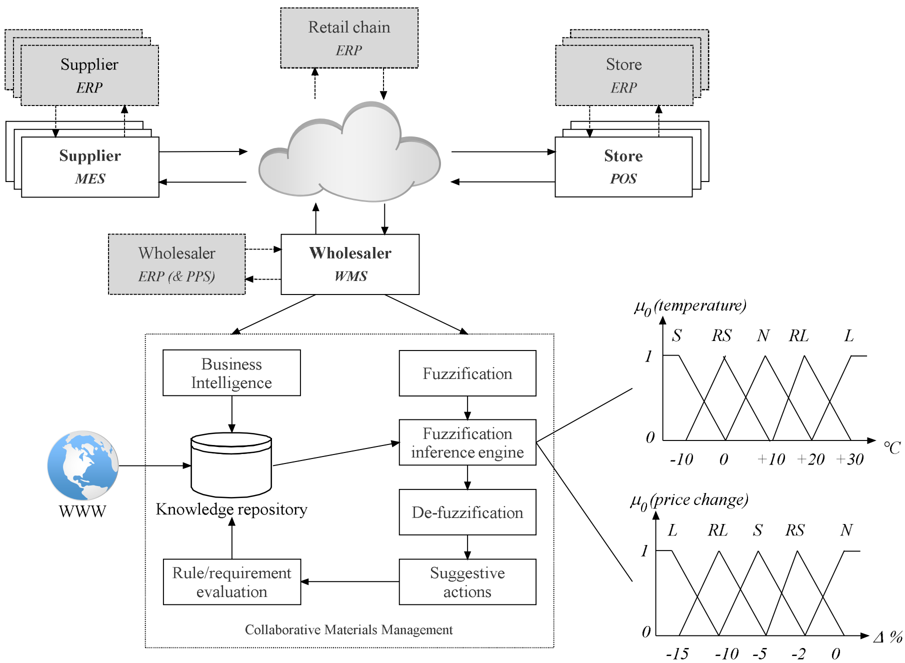
Creation of POS (3) and its Transfer across Supply Chain. POS is created and registered at an individual local database at each CR in each store (app. 1,100 for entire chain). Every three minutes, the POS is sent the store' back-office database, where it is consolidated with POS from the other 2-3 CRs in the store. This receipt-level POS is saved for three months and constantly deleted as time pass by, due to storage limitations. From here, the receipt POS is transferred to the ERP' database in each store which constantly aggregates with latest POS (aggPOS) cf. 3 minutes transfer interval. Here all sales data is saved on a native database, and this is the first time the store, retail chain and wholesaler can manually log on and access aggPOS data older than 3 months. Around midnight all aggPOS (amount per SKU per price per day) from all stores is transferred to the retail chain' database. From around 6-7 in the morning, procurement at retail chain can readily access the aggPOS in their ERP. Logging on to retail chain' ERP, wholesaler may also access the information. In Figure 1, from right to left.

To sum up, one of the main-findings is that the true demand (POS) is aggregated and only available in certain systems in batches and from certain time-points. This cause unstructured manual exceptions management (by phone) and reduces the ability to immediately react to changes in demand in stores. Further, wholesaler decides order quantity on two days' old demand-data influenced by 328 different stores' decision-making rather than real sales. This, albeit different information is available at different supply chain stages in real-time, hereunder demand at cash register (CR) in stores (i.e. point of sale (POS)), inventory levels at wholesaler and production status at supplier. Another main-finding is the time it takes to transfer and save aggPOS from stores to wholesaler through ERP – and the consequent delay before being available for decision-making. Since supplier produces FMPs down to hours before shipment, decreasing transfer time and sharing information directly between relevant systems (CR, WMS and MES) will increase the ability to react to demand changes. Further to this, retail stores manually control amounts of products available when determining order size, albeit having a pre-determined max-amount of each product. Given the low level of theft and waste (cf. close-to-expiration products sold at reduced price), inventory levels may be derived from ordered quantities subtracted POS with only weekly/periodic check. And chosen max-amounts may even further be evaluated cf. amount of products sold at reduced price is registered in POS.

5. Proposed Framework for Real-Time Information Sharing through Horizontal Integration

Not only does current systems integration make actual demand rather opaque, it also increases the risk of bullwhip effect. In literature, sharing of POS is argued as having positive impact on the supply chain performance, and a necessity for collaborative materials management [8, 13, 14]. To allow timely information sharing Figure 2 illustrates a conceptual model for integration of systems via horizontal integration, allowing decision-making based on real-time information sharing. Given wholesaler' role in the supply chain [5], the model assumes wholesaler to be coordinator of information and product flows. Information about demand (i.e. POS) and derived inventories from stores, production execution and status (i.e. MES) from supplier as well as inventories at wholesaler is shared in real-time.

Figure 2: Real-Time Information Sharing through Horizontal Integration



Based on this information, and (by store) pre-determined max-amounts in each store, wholesaler applies an ongoing fuzzification-process which is based on a knowledge repository (retrieving information from the web and business intelligence) and inference engine. E.g. if weather is expected to increase, then the derived expected consequence on demand is included in the suggestive actions. From this, the system will constantly evaluate ongoing demand and changes in demand (POS) against chances for changing already sent demand information to suppliers – filtered according to how far supplier is in production schedule.

If demand in stores sudden deviates, an alarm will occur informing the system about potential need for additional products (and vice versa, if no sale happens). Then, based on supplier' production status, the system will inform MES about additional/fewer quantities to be produced. Products which can be changed constantly follow open production orders in real-time. Thus if production of product A just finished, product A cannot be subject for any alteration. The further into the future the production is, the greater allowance for quantity changes. In this way systems across supplier (i.e. MES), wholesaler (i.e. WMS) and store (i.e. POS) will integrate horizontally, eliminating transfer through ERP. By allowing for "blanket" orders, the MES, WMS and CR will inform ERP about workload, opposite today, where ERP informs about workload. For reasons of speed, web-based information transfer is suggested.

6. Conclusion & Future Research Directions

The FMP production at suppliers is scheduled certain time after wholesaler sends order based on adjusted demand (i.e. wholesale order), despite actual sales is still recorded in stores – and it still runs while actual store orders are sent. No integration of planning and control systems challenges the timely information sharing [1, 2] with centrally adjusted demand [8]. By integrating the planning and control systems where demand information is created (MES, WMS and POS) across the supply chain then e.g. sudden changes to demand may be shared (near) live. Whether increase or decrease in demand it allows the entire triadic supply chain to react instantly and respond accordingly. This is particularly crucial for products processed each day e.g. ground beef/chicken/fish.

This research has focused on major common FMP-types in grocery industry in a conceptual model. More research is needed for other FMP-types to establish the validity in sharing POS in real-time and define what supply chain characteristics must be in place – when comparing against FMP with long shelf life. Also, the framework should be tested out empirically to investigate and quantify impact on service level across the supply chain, as well as ability to meet sudden changes in demand. The focus is regular demand, hence to test the generalizability, it would be favourable to test the model in different types of demand such as campaign, product introduction or seasonal demand. Also, this study has focused on franchise retail stores with decentralized decision-making. Additional research is needed for other store-types where centralized decision-making may be used such as corporate retail chain.

References

1. Simatupang, T.M., Sridharan, R.: An Integrative Framework for Supply Chain Collaboration. Int. J. Logist. Manag. 16, 257–274 (2005).
2. Simatupang, T.M., Sridharan, R.: The Collaboration Index: a Measure for Supply Chain Collaboration. Int. J. Phys. Distrib. Logist. Manag. 35, 44–62 (2005).
3. Jonsson, P., Holmström, J.: Future of Supply Chain Planning: Closing the Gaps Between Practice and Promise. Int. J. Phys. Distrib. Logist. Manag. 46, 62–81 (2016).

4. Fleischmann, B., Meyr, H., Wagner, M.: Advanced Planning & Structure of Advanced Planning Systems. In: Stadtler, H., Kilger, C., and Meyr, H. (eds.) Supply Chain Management and Advanced Planning. pp. 81–106. Springer Berlin Heidelberg, New York (2015).
5. Hübner, A.H., Kuhn, H., Sternbeck, M.G.: Demand and Supply Chain Planning in Grocery Retail: an Operations Planning Framework. Int. J. Retail Distrib. Manag. 41, 512–530 (2013).
6. Lusiantoro, L., Yates, N., Mena, C., Varga, L.: A Refined Framework of Information Sharing in Perishable Product Supply Chains. (2018).
7. Ferguson, M.E., Ketzenberg, M.E.: Information Sharing to Improve Retail Product Freshness of Perishables. Prod. Oper. Manag. 15, 57–73 (2006).
8. Alftan, A., Kaipia, R., Loikkanen, L., Sepns, K.: Centralised Grocery Supply Chain Planning: Improved Exception Management. Int. J. Phys. Distrib. Logist. Manag. 45, 237–259 (2015).
9. Swaminathan, J.M., Tayur, S.R.: Models for Supply Chains in E-Business. Manage. Sci. 49, 1387–1406 (2003).
10. Ettouzani, Y., Yates, N., Mena, C.: Examining Retail On Shelf Availability: Promotional Impact and a Call for Research. Int. J. Phys. Distrib. Logist. Manag. 42, 213–243 (2012).
11. Alfalla-Luque, R., Medina-Lopez, C., Dey, P.K.: Supply Chain Integration Framework Using Literature Review. Prod. Plan. Control. 24, 800–817 (2013).
12. Adebanjo, D.: Understanding Demand Management Challenges in Intermediary Food Trading: A Case Study. Supply Chain Manag. An Int. J. 14, 224–233 (2009).
13. Ståhl Elvander, M., Sarpola, S., Mattsson, S.: Framework for Characterizing the Design of VMI Systems. Int. J. Phys. Distrib. Logist. Manag. 37, 782–798 (2007).
14. Pramatari, K., Miliotis, P.: The Impact of Collaborative Store Ordering on Shelf Availability. Supply Chain Manag. An Int. J. 13, 49–61 (2008).
15. Danese, P.: Collaboration Forms, Information and Communication Technologies, and Coordination Mechanisms in CPFR. Int. J. Prod. Res. 44, 3207–3226 (2006).
16. Whipple, J.M., Russell, D.: Building Supply Chain Collaboration: a Typology of Collaborative Approaches. Int. J. Logist. Manag. 18, 174–196 (2007).
17. Cui, R., Allon, G., Bassamboo, A., Van Mieghem, J.A.: Information Sharing in Supply Chains: An Empirical and Theoretical Valuation. Manage. Sci. 61, 2803–2824 (2015).
18. Thatte, A.A., Rao, S.S., Ragu-Nathan, T.S.: Impact of SCM Practices of a Firm on Supply Chain Responsiveness and Competitive Advantage of a Firm. J. Appl. Bus. Res. 29, 499–530 (2012).
19. Choi, T.M., Li, J., Wei, Y.: Will a supplier benefit from sharing good information with a retailer? Decis. Support Syst. 56, 131–139 (2013).
20. Jonsson, P., Mattsson, S.-A.: The Value of Sharing Planning Information in Supply Chains. Int. J. Phys. Distrib. Logist. Manag. 43, 282–299 (2013).

21. Kumar, R.S., Pugazhendhi, S.: Information Sharing in Supply Chains: An Overview. Procedia Eng. 38, 2147–2154 (2012).
22. J.M., T., D.C., Y., M., B.: Exploring the Rationales for ERP and SCM Integration. Ind. Manag. Data Syst. 102, 26–34 (2002).
23. Mantravadi, S., Møller, C., Christensen, F.M.M.: Perspectives on Real-Time Information Sharing through Smart Factories: Visibility via Enterprise Integration. In: International Conference on Smart Systems and Technologies (SST): IEEE Region 8, Croatian Academy of Engineering. pp. 133–137 (2018).
24. Scheer, C., Theling, T., Loos, P.: Information Interface Classification of Actors in Supply Chains. Eighth Am. Conf. Inf. Syst. 36–40 (2002).
25. Møller, C.: ERP II: A Conceptual Framework for Next-Generation Enterprise Systems? J. Enterp. Inf. Manag. 18, 483–497 (2005).
26. Eisenhardt, K.M.: Building Theories from Case Study Research. Acad. Manag. Rev. 14, 532–550 (1989).

PAPER #6

Developing New Forecasting Accuracy Measure Considering Product's Shelf Life: Effect on Availability and Waste

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Role of PhD-candidate and declaration of authorship:
The PhD student defined the problem and proposed the structure and core scientific idea to solve it. The PhD student derived key-methodology, conducted case-study research and interviews, collected and analysed data, wrote the entire draft version of the paper, and re-vised it according to co-authors comments.

Developing New Forecasting Accuracy Measure Considering Product's Shelf Life: Effect on Availability and Waste

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Abstract. The purpose of this study is to propose a measure for evaluating forecast accuracy that incorporates the asymmetrical impact of fresh food products (FFP) shelf life. The proposed measure is compared against traditional forecast accuracy measures in terms of the effect on availability (i.e. fill-rate), inventory build-ing (i.e. freshness) and FFP expiration (i.e. waste). Case study of one of Denmark's largest grocery wholesalers was used to identify the asymmetrical impact of over-/under-forecasting for 17 FFPs, followed by a simulation to investigate the effect of using the proposed measure. Findings show that including the shelf life and the asymmetrical impact of over-forecasting with/without price reduction gives marginally lower fill-rate but an improved freshness of FFPs and a lower inventory level. This study adds to current literature on forecast accuracy measures by focusing on forecasts used for inventory control of short shelf life FFPs, where ensuring a high level of freshness and a low level of waste is critical.

Keywords: Perishable products, Forecasting accuracy, Food waste, Shelf life, Asymmetric loss

1. Introduction

Fresh food products (FFPs) represent nearly 25% of the total sale in the competitive grocery industry and is the fastest-growing product-segment (Nielsen, 2017, 2018). Consumers have high requirements for product availability, price, and quality/freshness (Jacobsen and Bjerre, 2015). Yet, 70% of consumers feel disappointed with FFPs' freshness and more than 80% with FFPs' availability in stores (BlueYonder, 2017). The short shelf life makes storing of FFPs inappropriate per se and must be considered in inventory control, to effectively reduce out-of-stock and increase freshness (Broekmeulen and van Donselaar, 2017; Eriksson et al., 2014).

This paper originates from a collaboration with the Danish branch of one of Scandinavia's largest gro-cery wholesalers. Interviews and analysis of their data revealed that inventory control of FFPs is particular-ly challenging when: 1) FFPs have so short shelf life that can be stored for only one day if even, 2) the reduced sales-price/waste causes a significant impact on revenue, 3) the demand varies for the following consecutive days, e.g. demand drop to zero for some days due to closing-days, holidays and vacations or demand drop to a (significantly) lower level for a certain period, e.g. weekend-products[16] or towards the ending of a campaign, and, 4) there is intermittent demand.

The literature suggests multiple inventory control models for perishable products, with fixed/continuous review period, fixed/random shelf life and stochastic/deterministic demand (Bakker et al., 2012; Goyal and Giri, 2001; Raafat, 1991; Silver et al., 1998; Steven Nahmias, 1982). The newsboy problem is considered particularly appropriate for products with one day shelf life (Silver et al., 1998), and two-period versions with stochastic demand are suggested (Nahmias and Pierskalla, 1973). However, they assume that demand follows a known distribution (e.g. normal distribution), although this is never the case in practice. Also, they do not link the demand forecasting with inventory control, leaving the two for iso-lated evaluation.

Forecasting demand is fundamental to inventory control in uncertain environments, and forecast accuracy affects the effectiveness of replenishment planning and subsequent levels of waste and quality (Adebanjo, 2009; Petropoulos et al., 2018; Teller et al., 2018). Accuracy is measured through the magnitude of deviations between actual demand and forecasted demand. Several different accuracy measures exist, mainly differing in how they penalize errors, e.g. absolute/relative/squared penalization. Widely used forecast accuracy measures in retail include mean forecast error (MFE), mean absolute percentage error (MAPE) and root mean squared error (RMSE) (Gneiting, 2011a; Gružauskas et al., 2019; Priyadarshi et al., 2019; Ramos et al., 2015). However, they assume that positive and negative deviations of the same magnitude have the same loss thus penalizing them symmetrically (Hyndman, 2006; Hyndman and Koehler, 2006; Kolassa, 2016; Kolassa and Schütz, 2007). The quantile loss function is a way to address this discrepancy since it allows differentiated penalization of over- and under-forecasting (Granger, 1999; Granger and Pesaran, 2000; Lee, 2007). Typically on the premise that under-forecasting (i.e. unavailability) is more critical than over-forecasting (i.e. inventory building) (Kourentzes et al., 2020; Trapero et al., 2019a). However, this premise does not

[16] Certain FFPs such as e.g. meat products (steaks, roasts, expensive cuts etc.) have significantly higher demand up to a weekend (Thursday, Friday and Saturday) but very low demand elsewise throughout the week.

always hold for FFPs. Under-forecasting may not always induce a greater loss. Some FFPs may be stored for a few days without losses, other FFPs may induce loss even after one day, and yet other FFPs may face rounds of price-reductions with stepwise losses. Perishability makes the pricing and cost structure more complex when trying to reduce the amount of waste while satisfying con-sumer requirements (Buisman et al., 2019; Chen et al., 2019; He et al., 2018). The impact depends on the shelf life in relation to the following days' demand. When an excessive amount (from over-forecasting) can be stored and absorbed by the coming days' demand – before the decrease in shelf life induces a loss from reduced sales price (or potential expiration) – the impact is smaller. After this time point, the effect will be much higher.

This paper proposes a forecasting accuracy measure which penalizes deviations asymmetrically considering the product's shelf life. It is compared against other accuracy measures such as RMSE, weighted MAPE (wMAPE) and weighted quantile loss (wQL), to evaluate its impact on the inventory (waste potential) and fill-rate (availability). This is investigated at a wholesaler through short term forecasting of retail store demand. This paper contributes to the existing literature on measuring forecasting performance by incorporating contextual insight about the FFP and its shelf life. This paper extends an earlier conference paper (Christensen et al., 2019) by proposing a new and improved forecasting measure and testing it more rigorously to an extended set of data, both in terms of products and testing-period. It provides understand-ing of asymmetrical forecasting evaluation according to shelf life and its relation to following days demand ensures high level of freshness and low level of waste. The developed accuracy measure overcomes short-comings from symmetrical evaluation (i.e. inventory building) and asymmetrical evaluation through only two thresholds (i.e. newsvendor problem). Further, the new measures seems beneficial for perishable prod-ucts characterized by: very short shelf life, expensive products where waste generates significant impact on revenue, demand with large variation across consecutive days, sensitive to closing days/holidays, erratic demand with sudden drops and/or intermittent demand.

2. Theoretical Background

Practitioners and systems strive towards a consistent and effective forecasting model selection by using a set of different accuracy measures. However, deciding on the "most accurate" forecasting model is not a straightforward task, and there is a general lack of trust in automatic model selection (Alvarado-Valencia et al., 2017). Further, it is found that human qualitative evaluation can outperform an automated algorithmic selection (Petropoulos et al., 2018). Yet, human evaluation for a wholesaler's product portfolio, typically with thousands of products, is a utopia, which in turn stresses the measures' essential importance.

Different statistical accuracy measures exist for evaluation of forecasting models (Hanke and Wichern, 2009; Hyndman, 2006; Hyndman and Koehler, 2006;

Kolassa, 2016; Mehdiyev et al., 2016), some appropriate for intermittent demand (Kolassa and Schütz, 2007). In a retail context, MFE, MAPE and (R)MSE are often used (see, e.g. Van Donselaar et al. (2016), Huber et al. (2017), Priyadarshi et al. (2019)). Table 1 depicts some of the most used penalization functions in forecasting accuracy measures and their valuation type; $P(\hat{y}_t, y_t)$ is the penalization of the deviations between forecasted demand, $\hat{y}_t$, and actual demand, y_t.

Table 1: Common penalization functions in forecasting accuracy measures, adapted from Gneiting (2011a)

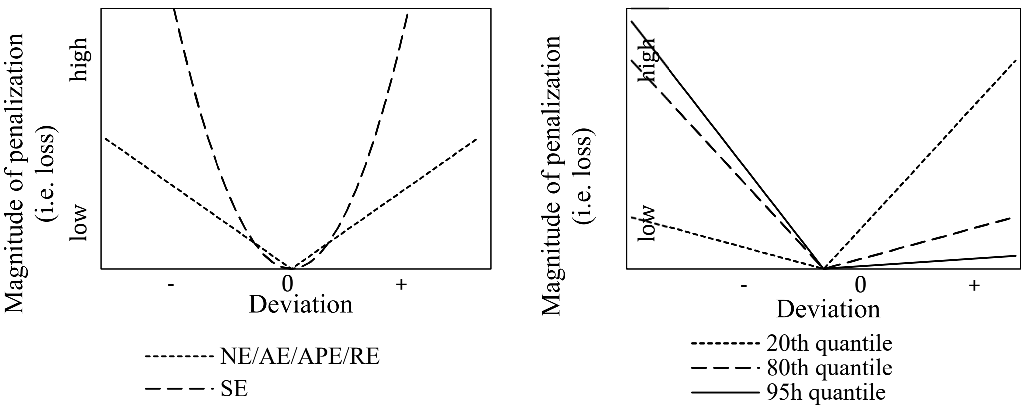
Symmetry	Penalization, $P(\hat{y}_t, y_t)$	Valuation type
symmetrical	$(\hat{y}_t - y_t)$	*normal error*
	$\lvert \hat{y}_t - y_t \rvert$	*absolute error*
	$(\hat{y}_t - y_t)^2$	*squared error*
	$\lvert (\hat{y}_t - y_t)/y_t \rvert$	*absolute percentage error*
	$\lvert (\hat{y}_t - y_t)/\hat{y}_t \rvert$	*relative error*
asymmetrical	$\begin{cases} \alpha \cdot \lvert \hat{y}_t - y_t \rvert & , if \quad \hat{y}_t \leq y_t \\ (1-\alpha) \cdot \lvert \hat{y}_t - y_t \rvert & , if \quad \hat{y}_t > y_t \end{cases}$ *where* $\alpha \leq 1$	*asymmetrical absolute error*

Note: $\hat{y}_t$ = forecasted demand, y_t = actual demand, α = penalization value

Since the normal error balances out the negative and positive deviations, it may have a summed devia-tion of 0, even though (several) large individual errors exist. The absolute error, absolute percentage error and relative error use absolute valuation, thereby cumulating deviations and overcoming the balancing out. While the squared error penalizes especially large deviations by squaring, the absolute percentage error and relative error" penalize deviations through relative impact to respectively actual or forecasted demand, making them scale independent. Hence, squared error may ignore the relative impact of deviations on loss-es when the demand is characterized by (high) variation. A variation of absolute percentage error - the weighted (mean) absolute percentage error (w(M)APE) – "considers percentage errors and weighs them by actual values" (Kolassa and Schütz, 2007, p. 41). When looking at multiple products and summarizing the performance across them, it results in more weight on larger deviations and less weight on smaller deviations. Otherwise, it standardizes the mean absolute error (MAE) by making it scale-independent. However, the main assumption when using wMAPE is the presence of a stationary demand which is not fulfilled when demand contains patterns (trend, seasonality, etc.) (Hyndman, 2006). The asymmetrical absolute error used in wQL evaluates (and penalizes) residuals according to a predetermined quantile where negative deviations are penalized by α and positive deviations by (1- α) (Aye et al., 2015; Gneiting, 2011b; Kourentzes et al., 2020; Trapero et al., 2019b, 2019a). It may be optimized and used as part of a control system for inventory planning and safety stock estimation (Syntetos et al., 2011). This makes it possible to reflect the desired service-level by setting the quantile equal to the fill-rate (Kolassa, 2016), hence, evaluating the forecast models by how well they fit the desired fill-rate.

Figure 1 illustrates the penalization functions for the accuracy measures across the size of the deviation. The left graph shows how penalization value increases for normal, absolute, squared, absolute per-centage and relative forecasting accuracy measures; either linearly or squared across the magnitude of the deviation with symmetrical impact. The right graph shows the asymmetrical absolute error through thresholds of 20th, 80th and 95th percentile and how penalization values do increase linearly, but with asymmetrical impact. While asymmetrical absolute error is typically optimized for a given fill-rate, its asymmetry may also represent the newsvendor problem. I.e. too many equals waste on a one-period basis, thereby entailing a higher penalization for over-forecasting than under-forecasting. The 20th quantile illustrates this, where over-forecasting is penalized four times more than under-forecasting, at the expense of lower fill-rate.

Figure 1: Penalization symmetry for different accuracy measures



Besides having multiple accuracy measures, it is important to note that a forecasting model may per-form well according to one measure, and perform poorly according to another. Kolassa (2020) points out that optimizing a forecasting model according to e.g. (R)MSE is equivalent to predicting the mean of the demand density distribution, while for MAE/wMAPE it is equivalent to predicting the median, and for wQL it is equivalent to predicting the quantile. Obviously, in the case of symmetrical demand density distribution, (R)MSE and MAE/wMAPE will yield the same result since identical median and mean. However, in practice, symmetrical density distributions are rarely evident. Hence rather than evaluating one forecasting model through different accuracy measures, different forecasting models should be evaluated for each accuracy measure. This would allow choosing a forecasting model according to the respective accuracy measures, rather than assuming that accuracy measures will point to the same optimal forecast-ing model.

3. Research Design

This study proposes an asymmetrical forecasting accuracy and investigates its value against other accuracy measures, by exploring the impact on inventory level (freshness) and fill-rate (availability) when forecasting the demand across a range of FFPs. Thus, the research design consists of three components: developing an asymmetrical accuracy measure (section 4), method application (section 5) and results from deploying the accuracy measure on empirical demand data (section 6).

Since the factors to consider in the asymmetrical forecast evaluation (e.g., shelf life and price reduction) should be appropriate for the (individual) FFPs in focus, it must be studied in-depth to gain an under-standing of the phenomenon (Eisenhardt, 1989). Thus, a case study was conducted at one of Scandinavia's largest grocery wholesalers distributing FFPs to more than 340 retail stores in Denmark through a central warehouse. The focus was on fresh meat/meat-free products as they deteriorate in only a few days (Evans, 2016), making them inappropriate for more days in inventory. Also, these products belong to the fastest growing product segment in the grocery market, i.e. FFPs (Nielsen, 2017, 2018), making them strategically important. Semi-structured interviews followed a protocol containing questions related to the processes of forecasting and ordering. The wholesaler forecasts the demand one day before the stores send actual orders and uses it as an order to the industrial supplier. The demand is forecasted as total store demand at a daily level considering the weekday-patterns.

4. Proposing an asymmetrical accuracy measure considering shelf life

Given FFPs' often short shelf life, compared to, e.g. dry goods, they deteriorate rapidly through time and are highly sensitive to impact from factors like seasons and weather – in terms of both demand and supply. This leaves FFPs with a latent uncertainty and particularly high variation in demand. Hence the risk of loss due to either reduced sales price or product expiration (Mena et al., 2011; de Moraes et al., 2020) is larger when over-forecasting, since not being able to sell excessive amounts before the critical product degradation. Vis-à-vis, when under-forecasting profit is lost. Figure 2 illustrates this by showing how the optimal quantity to order has the highest incremental profit (green line). For under-forecasting, lost sales results in a lower than optimal profit (blue line). Depending on the amount over-forecasted, the incremental profit becomes smaller and smaller for each time a price-reduction is required to sell products due to the short remaining shelf life (yellow and orange line). This happens iteratively until the FFPs finally expire, cause waste and diminish the profit (red line). This impact depends on the FFPs shelf life, since the longer shelf life, the slower deterioration, the more inventory days.

Figure 2: Impact from over-forecasting on profit

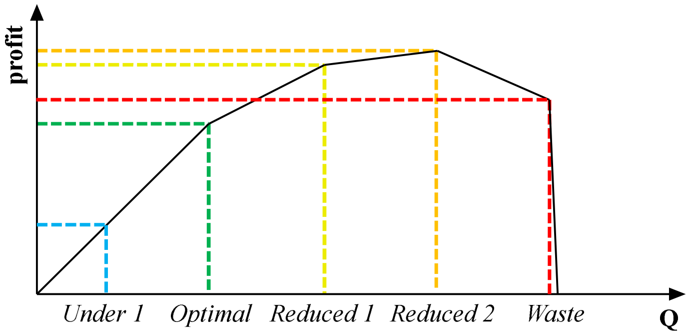
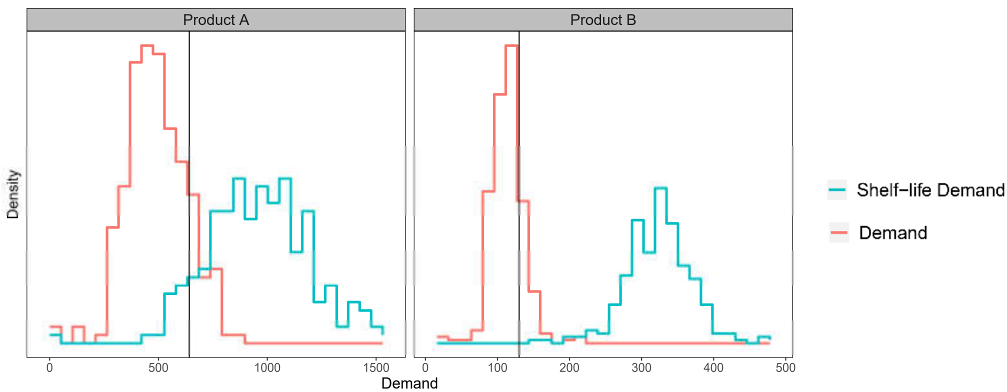


Figure 3 illustrates an example of two FFPs with their distributions for actual demand (red curve) and shelf life demand (green curve) for two different FFPs, and an indication of a fill-rate at q = 0.90 of the demand distribution (the black line in the graphs). The shelf life demand represents the sum of demand that can be absorbed from the FFPs in inventory within their shelf life. As an example, for an FFP with two days shelf life, shelf life demand is the demand that can be absorbed from the inventory within these two days. When the green shelf life demand curve overlaps the red demand curve (as for Product A), there may be situations where the inventory is higher than what is going to be sold within the FFP' shelf life, thereby causing waste. Thus, the less the overlap between the demand distribution (red line) and the shelf life demand distribution (green line), the less risk of facing waste (as for Product B).

Figure 3: Demand and shelf life demand distribution per fresh food product



At least four proposals have been made for inventory control of perishable products considering the lev-el of waste for products with up to few weeks shelf life, through an order-up-to policy: OIR policy (Duan and Liao, 2013), age-and-stock-based (CASB) policy (Lowalekar and Ravichandran, 2017) and EWA policy

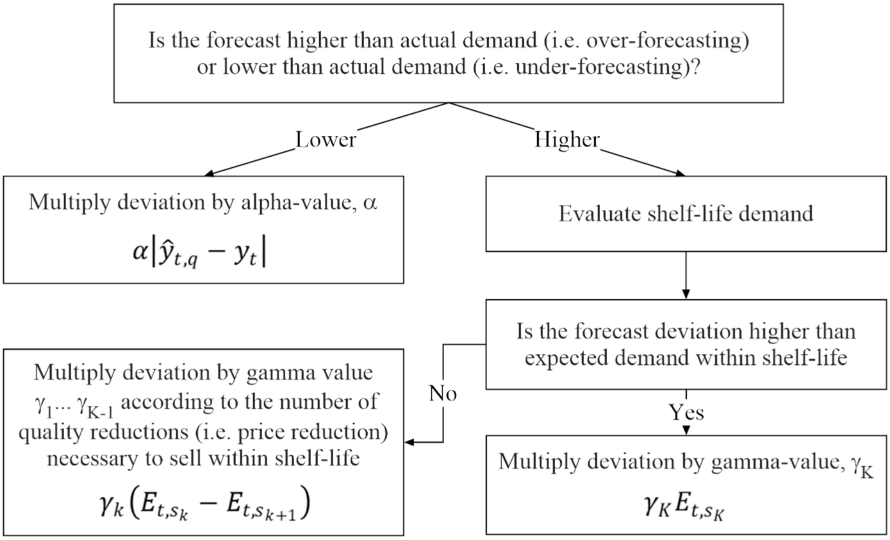
(Broekmeulen and van Donselaar, 2009; Kiil et al., 2018). The old inventory ratio (OIR), minimizes the expected quantity of expired products according to a predetermined out-of-stock allowance through two steps. First, it raises the inventory position to an order-up-to level. Then, when the ratio between expired products and total on-hand inventory is smaller than an accepted threshold, a quantity equivalent to expired products is ordered. The CASB policy follows a continuous review and suggests an order quantity when either the inventory position drops to a specified number of products (re-order point) or when the oldest batch has aged t units of time (Lowalekar and Ravichandran, 2017). The EWA policy includes the estimated number of expired products within the review period. Following Silver et al. (1998) EWA batch-es store orders according to case sizes with positive lead-times and weekly time-varying demand, as known in the grocery industry (Broekmeulen and van Donselaar, 2009). Kiil et al. (2018) extend this to EWASS and consider the size of safety stock relative to the expected number of expired products within the review period. However, they all assume a known demand distribution without relation to future demand forecast, which is not the case in practice. Subsequently, e.g. EWA assumes that in the case of sold-out, the prod-uct demand is lost without influencing any other product. Though in practice, substitution demand may occur (Gruen et al., 2002; Hübner, 2011), in turn impacting the demand outside the assumed demand distribution. The CASB assumes a sudden drop in quality (i.e. waste creation) without step-wise reduction, although this is not the case in practice (as discussed above).

To reflect the impact of FFPs' shelf life when evaluating forecast models, this study select a linear deterioration curve (Evans, 2016). This is well-used in practice and entails a same piecewise degradation of the FFP on daily basis. Depending on the shelf life left, the FFPs may be sold at full price or with a loss due to (several) price-reduction(s) or waste. To consider this, the weighted Shelf life Error (wSLE) is developed. Inspired by quantile loss, the wSLE splits the penalization across four types of thresholds:

5) under-forecasting causing reduced availability and lost revenue
6) over-forecasting where excessive FFPs are sold without a price reduction
7) over-forecasting where excessive FFPs are sold at a reduced price due to reduced shelf life; the price reduction may happen several times until the FFP eventually expires
8) over-forecasting where excessive FFPs cannot be sold within their shelf life, causing food waste.

The wSLE calculates the deviation's impact relative to its magnitude (scale-independent) and with penalization according to the decision-process in Figure 4. Depending on which threshold the deviation falls within, an α or γ penalization value is assigned respectively to the four types of thresholds.

Figure 4: Decision diagram for wSLE



Hence, the formulation of wSLE is as follows:

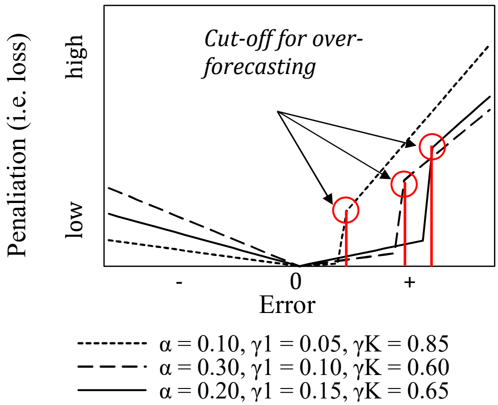
$$wSLE_q = \frac{\sum_{\{t \in T | y_t \geq \hat{y}_{t,q}\}} \alpha|\hat{y}_{t,q} - y_t| + \sum_{\{t \in T | y_t < \hat{y}_{t,q}\}} \sum_{k=1}^{K-1}\left(\gamma_k\left(E_{t,s_k} - E_{t,s_{k+1}}\right) + \gamma_K E_{t,s_K}\right)}{\sum_{t=1}^{n} y_t}$$

where:

- y_t is actual demand at time t and $\hat{y}_{t,q}$ is the forecasted demand at time t for quantile q
- α is penalization value if $\hat{y}_{t,q} \leq y_{,t}$ i.e. under-forecasting
- γ is penalization value if $\hat{y}_{t,q} > y_{,t}$ i.e. over-forecasting with penalties associated with the k price reductions of S, ranging from $\{\gamma_1, \dots, \gamma_K\}$ (see Figure 2)
- S is the number of days until the price reduction k occurs with s_K being the number of days until expiration, ranging from $\{s_1, \dots, s_K\}$ where $s_1 \leq s_2 \leq \cdots \leq s_K$
- $E_{t,s}$ is the inventory carried over to the day *t+s*, calculated as $\left(\hat{y}_{t,q} - C_{t,s}\right)^+$
- $C_{t,s}$ is the cumulative demand for time t and the next s days
- $\sum(\alpha + \gamma_1 + \gamma_2 + \cdots + \gamma_K) = 1$ and $\gamma_1 + \cdots + \gamma_{K-1} \neq \gamma_K$, since equal penalization of over-forecasting makes the weighted loss collapse to the qualtile loss function. Further, $\alpha \neq \gamma_1 + \cdots + \gamma_K$, since equal penalization of over-/under forecasting makes the function collapse to conventional symmetrical penalization.

Figure 5 provides three examples of the loss function for wSLE with three thresholds, where it is evi-dent that although under-forecasting is penalized up to three times more than over-forecast without price-reduction/waste, then over-forecasting with price-reduction/waste is penalized. This causes an asymmetrical penalization with three thresholds, thereby overcoming the challenges of (a)symmetrical measures to consider the impact of shelf life. Thus, the wSLE considers the impact of shelf life on FFPs, where over-forecasting without losses is penalized significantly lower than over-forecasting causing losses, and, loss from under-forecast is evaluated relative to the loss from over-forecasting (causing expired FFPs).

Figure 5: Penalization symmetry for accuracy measure wSLE considering shelf life, example with thresh-olds



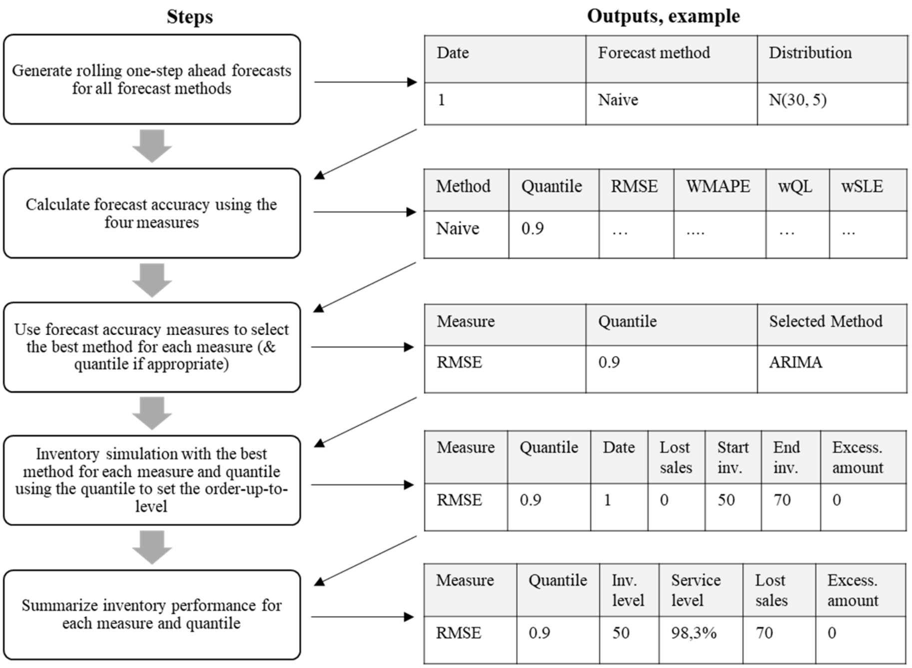
5. Method Application

Seventeen fresh meat/meat-free products were selected. The selection-criteria include normal demand eve-ry day, less than three weeks total shelf life, one of four primary meat types (beef/pork/chicken/fish) and mature product life cycle stage. To ensure enough demand data for forecasting, evaluating and comparing the wSLE against other measures across a year's demand pattern, e.g. annual seasons, twelve months de-mand data was used. Since promotions and campaigns impact the choice of forecasting model (Bojer et al., 2019), hence also the measure evaluation, such demand data was cleansed from the demand data.

The average daily demand of the 17 FFPs is between 29 and 602 units, with the maximum allowed day in inventory ranging between one day and six days. Specifically, nine FFPs with one storage day, four with two days, three with three days and one with six days. In terms of shelf life demand (Figure 3), seven FFPs do not overlap (i.e. less risk of waste), while ten FFPs overlap (i.e. increased risk of waste).

To evaluate the wSLE, a rolling forecast is generated, which is optimized for different fill-rates with a range of different forecasting models and then calculate the accuracy through four selected measures. After selecting the best performing forecasting model for each measure and quantile, the inventory records are simulated for the period to sum up the inventory performance. Figure 6 summarizes the method appli-cation with an example of output from each step.

Figure 6: Overview of processes of measure evaluation



5.1. Forecasting models

Several different qualitative and quantitative forecasting models exist for forecasting product demand in the retail context, mainly differentiating according to demand type (normal, seasonal or campaign) (see, e.g. Bojer et al. (2019), Huber (2017), Fildes et al. (2018)). This study uses quantile forecast optimized for *q={0.80, 0.85, 0.90, 0.95}* (Gneiting, 2011b) and choose seven forecasting models to test and evaluate the accuracy measures upon for the 17 FFPs. The forecasting models range from simple models such as naïve, naïve with seasonality and moving average (Hanke and Wichern, 2009) to more complex models such as ARIMA (Hyndman and Khandakar, 2008), theta (Assimakopoulos and Nikolopoulos, 2000), ETS (Hyndman et al., 2008) and a combination model. The combination model is the arithmetic mean value from ARIMA, theta and ETS.

The literature discusses several different approaches to effective forecasting model selecting. These approaches range from rather simple ones such as, e.g. coefficient of variation (R2) to more advanced ones such as, e.g. Akaike Information Criterion (AIC) which balances the forecasting model's fitness and complexity (Akaike, 1974). A more straightforward approach is the cross-validation of model accuracy across a training-set (in-sample) and a test set (out-of-sample). Cross-validation is applied by dividing the time series into s subsets, where the model is tested s times upon each s-1 subsets as a training-set (in-sample), and the one remaining subset for testing the accuracy of the model (out-of-sample), until all s subsets have been tested as out-of-sample (Kourentzes et al., 2019). The forecasting model with highest out-of-sample accuracy is then selected. In this way, each FFP will have one forecast model selected for each forecast accuracy measure.

We use the statistical programming language R and R packages **forecast** (Hyndman et al., 2019) and **fable** (O'Hara-wild et al., 2020) for forecasting, where R automatically optimizes the models for their different parameters.

5.2. Forecasting accuracy measures

This study uses the symmetrical accuracy measures RMSE and wMAPE. Both are used widely in evaluating demand forecast of perishable products (Huber et al. (2017), Ramos et al. (2015), Priyadarshi et al. (2019)). The accuracy measures are formulated as follows, for the different quantile forecast distributions q.

$$RMSE_q = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{y}_{t,q} - y_t\right)^2}$$

$$wMAPE_q = \frac{\sum_{t=1}^{n}\left|\hat{y}_{t,q} - y_t\right|}{\sum_{t=1}^{n} y_t}$$

To include asymmetry in the evaluation, wQL is included based on the asymmetrical accuracy function (Gneiting, 2011b). A scale-independent variation weighted Quantile Loss (wQL) is used. The wQL is formulated as follows, where deviations at time $\hat{y}_{t,q} \leq y_t$ are penalized by α, and by $(1-\alpha)$ at time $\hat{y}_{t,q} > y_t$. The α-value is chosen according to the four quantiles used, i.e. for wQL_q then $\alpha = q$.

$$wQL_q = \frac{\sum_{\{t\,\in\,T|y_t\,\geq\,\hat{y}_{t,q}\}}\alpha\left|\hat{y}_{t,q} - y_t\right| + \sum_{\{t\,\in\,T|y_t\,<\,\hat{y}_{t,q}\}}(1-\alpha)\cdot\left|\hat{y}_{t,q} - y_t\right|}{\sum_{t=1}^{n} y_t} \quad ;\ \alpha \leq 1$$

When using the developed weighted Shelf life Error (wSLE), for reasons of simplicity, the following applies three thresholds, and thus no stepwise price reduction. Table 2 lists the chosen values for α, γ_k and γ_K and the specified fill-rates for the different FFPs. These values are set through qualitative decision-making by the procurement department at the wholesaler based on their in-depth domain knowledge. Table 3 depicts three examples of reasons for the choice of penalization across the thresholds.

Table 2: Penalization factors for fresh meat/meat-free products

#	**Product**	**Under-forecasting, α**	**Over-forecasting (no price reduction), γ_k**	**Over-forecasting (price reduction), γ_K**	**Desired fill-rate**
1	Ground beef, 8-12%	*0.30*	*0.10*	*0.60*	*99.0%*
2	Ground beef, 4-7%	*0.35*	*0.10*	*0.55*	*99.0%*
3	Diced beef	*0.25*	*0.5*	*0.70*	*98.0%*
4	Ground pork, 8-12%	*0.35*	*0.10*	*0.55*	*99.0%*
5	Pork chops	*0.30*	*0.10*	*0.60*	*98.5%*
6	Organic ham schnitzel	*0.35*	*0.10*	*0.55*	*98.0%*
7	Organic pork tenderloin	*0.25*	*0.5*	*0.70*	*98.0%*
8	Chicken breast	*0.30*	*0.5*	*0.65*	*99.0%*
9	Whole chicken	*0.40*	*0.10*	*0.50*	*99.0%*
10	Ground fish	*0.30*	*0.30*	*0.40*	*98.0%*
11	Salmon filets	*0.30*	*0.15*	*0.55*	*98.5%*
12	Pork tenderloin	*0.35*	*0.10*	*0.55*	*98.5%*
13	Ground pork/cattle, 8-12%	*0.30*	*0.5*	*0.65*	*99.0%*
14	Organic sausage	*0.30*	*0.30*	*0.40*	*98.0%*
15	Meat-free soy-based minced	*0.25*	*0.5*	*0.70*	*98.0%*
16	Meat-free soy-based falafel	*0.25*	*0.5*	*0.70*	*98.0%*
17	Meat-free soy-based chicken	*0.20*	*0.5*	*0.75*	*98.0%*

Table 3: Comments to forecasting evaluation and shelf life information for fresh meat/meat-free products

#	**Product**	**Comments, under-forecasting**	**Comments, over-forecasting**
3	Diced beef	Considered a special product and not critical to assortment, i.e. greater acceptance if out-of-stock. Demand is medium and unforeseen demand may result in some stores not receiving products. Yet since special product, wholesaler allows smaller service-level.	Since short shelf life, over-forecasting without price reduction results in a relatively larger decrease in freshness (14% per day). Over-forecasting with price-reduction/loss results in relatively larger loss than other products given the product price.
9	Whole chicken	Essential to assortment and availability is critical. Demand is large and unforeseen demand usually allows all stores to receive some products (i.e. not necessarily full delivery for all stores). Since demand is stable, no buffer-stock is maintained, making an impact from under-forecasting large.	Since short shelf life, over-forecasting without price reduction results in a relatively larger decrease in freshness (13% per day). Over-forecasting with price-reduction results in relatively larger loss than other products given the amounts.
10	Ground fish	Important to assortment and availability is important. Demand is medium and	Since particularly short shelf life, both over-forecasting with and without

#	Product	Comments, under-forecasting	Comments, over-forecasting
		unforeseen demand may result in some stores not receiving products. Yet given this and the short shelf life, wholesaler allows smaller service-level.	price-reduction results in a large decrease in freshness (20% per day) with a smaller chance of selling to stores due to consumer perception.

From the different penalization values, it is evident that over-forecasting causing either price reduction or waste is significantly harder penalized than over-forecasting not causing price reduction. Further, that under-forecasting seems to fluctuate around the mean impact from both types of over-forecasting. The specified fill-rate indicates a requirement for a high level of availability, which may seem to contradict the relative low penalization for under-forecasting. However, given the different factors for penalization, there is an overall primary goal of ensuring a low level of food waste and associated costs.

To test the sensitivity of the penalization values of wSLE, they are adjusted by +/- 20% for under-forecasting and over-forecasting causing price-reduction. When testing the sensitivity for e.g. over-forecasting with price-reduction, the ratio between under-forecasting and over-forecasting without price-reduction remains the same, thereby allowing explicit testing of the sensitivity for over-forecasting.

5.3. Evaluation of impact from accuracy measures

To investigate the impact of the individual accuracy measure on choosing a forecasting model, this study simulate the inventory behaviour as a consequence of suggested order quantities (based upon $\hat{y}_{p,t,q}$) for each FFP for each day. The simulations are run across the entire period (twelve months), and start each day by refitting the chosen forecasting model and then updating the forecast for a given FFP. The output of the forecasting process is a forecast distribution, $F_{p,t}$, for each FFP p at time t. To determine the order quantity, this study use the order-up-to level (OUL) (as discussed in theoretical background) based on the desired fill-rate, which is the quantile of the forecast distribution: $OUL_{p,t,q} = quantile\left(F_{p,t}, q\right)$. Since determining the OUL according to quantiles, rather than mean demand, a buffer is included in the forecasted demand $\hat{y}_{p,t,q}$. In this way $OUL_{p,t,q}$ may be forecasted demand ($\hat{y}_{p,t,q}$), or ending inventory from the day before ($I_{ending,p,t-1}$). In this study $I_{ending,p,t} = OUL_{p,t,q} - y_{p,t}$. For reasons of simplicity, 100% delivery from suppliers is assumed ($Q_{ordered,p,t,q} = Q_{delivered,p,t,q}$) to exclude noise from reduced/missing deliveries. The order quantity is accordingly determined by subtracting the inventory level from the OUL (i.e. $\hat{y}_{p,t,q}$) when $\hat{y}_{p,t,q} > I_{ending,p,t-1}$, or is 0, when can be covered from inventory.

$$Q_{ordered,p,t,q} = \begin{cases} OUL_{p,t,q} - I_{ending,p,t-1} & , \quad if\ \hat{y}_{p,t,q} > I_{ending,p,t-1} \\ 0 & , \quad if\ \hat{y}_{p,t,q} \leq I_{ending,p,t-1} \end{cases}$$

Shelf life is used as a constraint to determine the impact from the forecasting model on inventory and fill-rate, hence FFP freshness and availability. Moreover, by using shelf life through the maximum allowed nights an FFP can stay over at wholesaler, one can determine when an excessive number of FFPs from over-forecast may or may not result in sales with/without price-reduction.

The inventory performance is assessed through the following four parameters for each of the FFPs, given the different quantiles for forecasting: (1) fill-rate ($FR_{p,q}$) (Huber et al., 2017), is the percentage of FFPs delivered to store out of ordered; (2) lost sales ($LS_{p,q}$) – the percentage of FFPs not delivered to stores; (3) average inventory level as a percentage of the actual demand ($ID_{p,q}$) – the mean value of ending inventories; (4) percentwise excessive amount in inventory from over-forecast ($Waste_{p,q}$) – the sum of FFPs from OUL which cannot be absorbed by the following days' shelf life demand.

$$FR_{p,q} = 1 - \frac{1}{n}\sum_{t=1}^{n} \frac{min\left(OUL_{p,t,q}, \hat{y}_{p,t}\right)}{y_{p,t}}$$

$$LS_{p,q} = 1 - SL_{p,q}$$

$$ID_{p,q} = \frac{\frac{1}{n}\sum_{t=1}^{n}\left(max\left(I_{ending,p,t-1,q}, OUL_{p,t,q}\right) - Q_{store,p,t,q}\right)}{\sum_{t=1}^{n} y_t}$$

$$Waste_{p,q} = \frac{\sum_{t=OUL_{p,t,q}>\sum_{T=t}^{T+S}\hat{y}_{p,t,q}}^{n}\left(OUL_{p,t,q} - \sum_{T=t}^{T+S}\hat{y}_{p,t,q}\right)}{\sum_{t=1}^{n} y_t}$$

6. Results

Table 4 provides a summarized overview of the performance values for the different measures and quantiles for all 17 FFPs. For a product-level overview, please see Appendix 1. Additionally, Table 4 provides results from the sensitivity testing of the penalization values of wSLE (light blue area). Bold numbers represent best performance for the given q, while bold italic numbers represent best performance for the given q in each of the four sensitivity scenarios. E.g., for wSLE sensitivity scenario 1, wSLE still performs best (compared to wMAPE, RMSE and wQL) in inventory/demand and waste for $q = \{0.85, 0.90, 0.95\}$.

Table 4: Summarized performance for all FFPs, accuracy measures and quantiles

Measure	*q*	Inventory/ demand (%)	Waste (%)	Fill-rate (%)	Lost sales (%)
wMAPE	0.80	15.34	0.80	96.89	3.11
	0.85	18.10	0.87	97.51	2.49
	0.90	22.11	0.99	98.12	1.88
	0.95	28.82	1.21	98.76	1.24
RMSE	0.80	**14.95**	0.76	96.80	3.20
	0.85	17.62	0.83	97.43	2.57
	0.90	21.62	0.95	98.06	1.94
	0.95	28.30	1.17	98.73	1.27
wQL	0.80	19.47	1.03	**97.48**	**2.52**
	0.85	22.92	1.17	**98.13**	**1.87**
	0.90	27.42	1.37	**98.74**	**1.26**
	0.95	34.68	1.74	**99.27**	**0.73**
wSLE penalization as determined by case study	0.80	15.43	**0.74**	96.96	3.04
	0.85	**17.29**	**0.80**	97.41	2.59
	0.90	**20.74**	**0.93**	98.00	2.00
	0.95	**26.96**	**1.14**	98.64	1.36
wSLE sensitivity scenario 1 +20% penalization for over-forecasting with price reduction, equal proportions	*0.80*	*15.24*	***0.74***	*96.91*	*3.09*
	0.85	***17.26***	***0.80***	*97.41*	*2.59*
	0.90	***20.71***	***0.93***	*98.00*	*2.00*
	0.95	***26.99***	***1.14***	*98.64*	*1.36*
wSLE sensitivity scenario 2 -20% penalization for over-forecasting with price reduction, equal proportions	*0.80*	*15.37*	***0.74***	*96.96*	*3.04*
	0.85	***17.26***	***0.80***	*97.41*	*2.59*
	0.90	***20.71***	***0.93***	*98.00*	*2.00*
	0.95	***26.96***	***1.14***	*98.64*	*1.36*
wSLE sensitivity scenario 3 +20% penalization for under-forecasting, equal proportions	*0.80*	*15.89*	***0.75***	*97.07*	*2.93*
	0.85	***18.76***	***0.82***	*97.66*	*2.34*
	0.90	***22.04***	***0.93***	*98.16*	*1.84*
	0.95	***27.09***	***1.14***	*98.66*	*1.34*
wSLE sensitivity scenario 4 -20% penalization for under-forecasting, equal proportions	*0.80*	*14.91*	***0.74***	*96.83*	*3.17*
	0.85	***16.70***	***0.80***	*97.29*	*2.71*
	0.90	***20.68***	***0.93***	*97.99*	*2.01*
	0.95	***26.96***	***1.14***	*98.64*	*1.36*

In general, the results confirm the trade-off between high fill-rate (wQL) and low waste (wSLE), both at product and aggregated level. This, by wSLE consistently performing best in terms of waste, and wQL in terms of fill-rate. Although this in itself is not surprising (considering how deviations are penalized differently), the wSLE offers a new way of evaluating both the forecasting inaccuracy and the inventory when considering waste. In terms of overall impact (Table 4), it seems that wQL outperforms the other measures by ensuring a consistently higher fill-rate up to 99.27% (*q =0.95*). However, when comparing wQL against wSLE, e.g. the 0.63% higher fill-rate entails 52.6% more waste and 28.6% higher average inventory level at *q=0.95* (see grey marked numbers). In fact, for all *q* wSLE has the lowest number of excessive FFPs while wQL has the highest. Further, wQL also increases the most in excess across quantiles.

In terms of chosen forecasting models (Appendix 1), the same forecasting model may be suggested for different accuracy measures, e.g. for FFP 9 and 11, wMAPE, RMSE and wSLE choose the combination model. Hence for these FFPs, wSLE offers no disparate impact. However, it is worth noticing that wSLE, as well as wMAPE and RMSE, outperform the wQL and its asymmetrical evaluation by ensuring lower inventory level and waste. Further, wSLE is interestingly the only accuracy measure differentiating in suggested forecasting models for q={0.80, 0.85, 0.90, 0.95}, with two/three different forecasting models for 10 out of the 17 FFPs. While RMSE and wMAPE per se do not select a quantile-specific forecasting model since using squared/absolute penalization, wQL does. However, that only wSLE and not wQL differentiates in the actual selection of forecasting models can be attained that wQL searches for accurate estimation of point forecasting according to lowest cost, not taking into account the possibility of waste, whereas wSLE considers the level of waste.

7. Discussion

In retail context, multiple accuracy measures are highlighted for evaluating forecasts, mainly applying a symmetrical consideration of over- and under-forecasting (Van Donselaar et al., 2016; Huber et al., 2017; Priyadarshi et al., 2019). While wQL focuses on attaining a high fill-rate (Gneiting, 2011b), it is at the expense of excessive amounts and an increase in inventory levels. From the study, wMAPE and RMSE are better than wSLE (and wQL) in inventory level at q = {0.80}, yet it is only marginal compared to the significantly higher level of lost sales. Further, while wMAPE and RMSE perform better than wSLE in terms of fill-rate and lost-sales at different quantiles, it is at the risk of more waste and inventory. Contrary, for wSLE, the focus is on ensuring a low level of waste at the expense of rather under-forecasting, while only penalizing the absorbable excessive number of FFPs very little. In terms of shelf life, this also means that wSLE ensures a significantly higher level of freshness in the FFPs, where wQL results in the highest number of days in inventory, i.e. lowest freshness. Putting this in relation to waste and total sales, for more than half of the FFPs, the wSLE has the lowest number of FFPs being sold at a reduced price, deductively ensuring the freshest FFPs. For the FFPs 3, 6, 7, 8 and 13, there is no excess.

As for the sensitivity testing, i.e. wSLE scenario 2-5, the performance is almost the same and wSLE still outperforms the other accuracy measures in terms of excessive amounts (i.e. waste), by consistently choosing the forecasting model causing the lowest amount of waste. As expected, when increasing the penalization for over-forecasting or decreasing the penalization for under-forecasting (i.e. emphasizing waste), lower inventory levels are obtained at the expense of higher lost sales. Vice versa, when decreasing the penalization for over-forecasting or increasing the penalization for under-forecasting (i.e.

emphasizing availability), higher inventory levels are obtained, at the expense of lower lost sales. By attaining a focus on waste and penalizing over-forecasting causing waste higher, there will be less products sold on discount. Given the impact on inventory level also, products will be less in inventory before sold, thereby increasing the freshness. In this study, the wSLE is considered at a product level, testing the impact across 17 FFPs. The penalization values may also be applied at group level, e.g. according to animal type or customer groups. In this way the penalization in wSLE may reflect e.g. different managerial dispositions as to how waste (i.e. over-forecasting) should be penalized compared to fill-rate (i.e. under-forecasting). Further, by applying the penalization at product-group level, implications in determining three (or more) penalization values also reduce.

Summing up, although wSLE sometimes chooses the same forecasting models as other accuracy measures, it is shown that wSLE is the only accuracy measure that consistently results in lowest waste and inventory level. Furthermore, wQL is the only asymmetrical accuracy measure that consistently results in higher inventory level and risk. Despite wQL has higher performance in fill-rate, it causes relatively more waste, indicating a non-proportional development in the performance. Based on the analysis and results, the trade-off between availability and freshness impacts the performance rather significantly. Hence, the wSLE overcomes the shortcoming from the symmetrical evaluation (i.e. inventory building) and asymmetrical evaluation through only two thresholds (i.e. newsvendor problem). Also, it confirms the importance of considering the over-forecasting when waste is relatively low compared to relatively high. The wSLE is expected to reduce losses from waste, price-reduction and excessive inventory levels, by generally ensuring more fresh products in inventory for short amount of time. In turn, it is expected that this will entail more fresh products, which ultimately may lead to increased sales, considering the consumer focus on freshness.

Although, the results may seem low (i.e. little percentwise change in performance), this study includes only 17 FFPs. If deploying wSLE across an entire assortment (with up to hundreds of FFPs), the impact is considered big. Also, the results from this study reflect a combined performance from forecasting accuracy including the consequent inventory control. This makes it relevant to other studies (Broekmeulen and van Donselaar, 2009; Kiil et al., 2018) focusing only on the inventory aspect.

8. Conclusion

Widely used forecasting accuracy measures reflect a symmetrical evaluation of over- and under-forecasting, entailing that the derived losses have same impact and only dependent on the magnitude of the deviation. This is challenging for FFPs since the impact from waste on profit is higher than from reduced fill-rate. This paper investigates asymmetrical evaluation of forecasting accuracy and how this impacts both availability and freshness. Although asymmetrical measures are proposed, symmetrical ones are still extant used in FFP context. Also, even though wQL differentiates the evaluation of over- and under-forecasting, it does not consider explicitly the issue of the asymmetrical impact of over-forecasting in relation to shelf life, i.e. (no) price-reduction and waste. This study develops an asymmetrical accuracy measure considering demand during the shelf life of the product based on an empirical case study. The proposed wSLE measure considers under-forecasting, over-forecasting with no reduction in profit and over-forecasting causing losses (i.e. price reduction and/or obsolescence). The wSLE ensures a differentiated penalization at the product level. The study adds to current literature on forecasting accuracy measures by focusing on shelf life and its relation to the following days demand to ensure a high level of freshness and low level of waste. Both by developing wSLE and by further examining and comparing with other well-known accuracy measures. The main findings are that the proposed wSLE seems beneficial for perishable products (in particular FFPs) characterized by very short shelf life, expensive products where waste generates a significant impact on revenue, demand with large variation across consecutive days, sensitive to closing days/holidays, erratic demand with sudden drops and/or intermittent demand.

This study shows that managers must consider how their choice of forecasting accuracy measures impacts the inventory performance of perishable products since current accuracy measures do not include the risk of waste. However, particularly two implications seem relevant for the practical and managerial application. First, determining the specific penalization values may be challenging across an entire assortment with hundreds of different FFPs. Further, depending on where these values are to be reinforced, geographical/sociological differences may result in different perceptions of the quality of the products, thereby differences in penalization for forecasting for different product groups and/or customers. In turn, for large differences, this may require forecasting to be disaggregated to a lower level encompassing such different perceptions (i.e. penalization values). Second, applying wSLE versus other well-knowns requires an active managerial positioning towards increasing freshness of food and reducing food waste and excess inventories. Even though wSLE reduces the fill-rate slightly compared to those accuracy measures ensuring high fill-rate – it reduces the inventory and increases freshness relatively more.

For future research, this study should be widened to include more cases to investigate the robustness of wSLE in terms of waste and availability from the suggested forecasting model in different contexts (e.g. fashion industry where price reductions are frequent towards the end of a season until having sold out of inventory). The wSLE may be applied to other case studies rather straightforward by changing the penalization values (for respectively over- and under-forecasting), the number of days until a (further) price reduction occurs and the number of times a product may have a price reduction before it is completely wasted. Depending on the context specifics, other price reduction curves may be appropriate. Related to this, although delimited from this study, future research could also benefit from developing a model for automatically determining the penalization values upon e.g. financial aspects related to price-reductions, handling costs, ordering costs etc., so that the piecewise penalization reflects the underlying financial impact also. Also, interest would be in investigating the wSLE according to product-/customer-specific penalizations which may be set at a product group level according to e.g. type of FFP or customer group, thereby ensuring a differentiated penalization of the forecasting accuracy. Also, there is a need for investigating optimal ordering decisions for inventory control of FFP's using wSLE, as this study only addresses better forecast model selection, and not optimal ordering decision to minimize the wSLE. Further, since more prone to intermittency and variation in demand at the store level, it is of interest to validate wSLE at retail stores as it is expected to demonstrate an even larger reduction in waste. Finally, as opposed to this study where the impact is considered linear, other contexts may impose a non-linear impact. As an example, the impact from over-/under-forecasting within hospital sector (e.g. not having blood for one patient versus ten patients) or environmental impact (e.g. small versus large CO_2 emission) may entail exponentially more penalization on larger deviations than minor deviations. Thus, future research could investigate how an exponential or quadratic penalization for deviations will impact the choice of forecasting model and thus level of availability and waste.

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References

Adebanjo, D. (2009), "Understanding Demand Management Challenges in Intermediary Food Trading: A Case Study", Supply Chain Management: An International Journal, Vol. 14 No. 3, pp. 224–233.

Akaike, H. (1974), "A New Look at the Statistical Model Identification", IEEE Transactions on Automatic Control, Vol. 19 No. 6, pp. 716–723.

Alvarado-Valencia, J., Barrero, L.H., Önkal, D. and Dennerlein, J.T. (2017), "Expertise, Credibility of System Forecasts and Integration Methods in Judgmental Demand Forecasting", International Journal of Forecasting, Elsevier B.V., Vol. 33 No. 1, pp. 298–313.

Assimakopoulos, V. and Nikolopoulos, K. (2000), "The Theta Model: A Decomposition Approach to Forecasting", International Journal of Forecasting, Vol. 16 No. 4, pp. 521–530.

Aye, G.C., Balcilar, M., Gupta, R. and Majumdar, A. (2015), "Forecasting Aggregate Retail Sales: The Case of South Africa", International Journal of Production Economics, Elsevier, Vol. 160, pp. 66–79.

Bakker, M., Riezebos, J. and Teunter, R.H. (2012), “Review of Inventory Systems with Deterioration Since 2001”, European Journal of Operational Research, Elsevier B.V., Vol. 221 No. 2, pp. 275–284.

BlueYonder. (2017), Customer Experience in Grocery Retail: The Fresh Opportunity Customers in Fresh - A Global Survey of 4,000 Consumers Shine Light on Customer Experience in Fresh and Product Availability.

Bojer, C.S., Dukovska-Popovska, I., Christensen, F.M.M. and Steger-Jensen, K. (2019), “Retail Promotion Forecasting: A Comparison of Modern Approach”, in Ameri, F., Stecke, K.E., Cieminski, G. von and Kiritsis, D. (Eds.), Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part I, Springer, pp. 575–582.

Broekmeulen, R.A.C.M. and van Donselaar, K.H. (2009), “A Heuristic to Manage Perishable Inventory with Batch Ordering, Positive Lead-Times, and Time-Varying Demand”, Computers and Operations Research, Vol. 36 No. 11, pp. 3013–3018.

Broekmeulen, R.A.C.M. and van Donselaar, K.H. (2017), “Quantifying the Potential to Improve on Food Waste, Freshness and Sales for Perishables in Supermarkets”, International Journal of Production Economics, Elsevier Ltd, No. October, pp. 1–9.

Buisman, M.E., Haijema, R. and Bloemhof-Ruwaard, J.M. (2019), “Discounting and Dynamic Shelf Life to Reduce Fresh Food Waste at Retailers”, International Journal of Production Economics, Elsevier Ltd, Vol. 209, pp. 274–284.

Chen, X., Wu, S., Wang, X. and Li, D. (2019), “Optimal Pricing Strategy for The Perishable Food Supply Chain”, International Journal of Production Research, Vol. 57 No. 9, pp. 2755–2768.

Christensen, F.M.M., Dukovska-Popovska, I., Bojer, C.S. and Steger-Jensen, K. (2019), “Asymmetrical Evaluation of Forecasting Models through Fresh Food Product Characteristics”, in Ameri, F., Stecke, K.E., Cieminski, G. von and Kiritsis, D. (Eds.), Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part II, Springer, pp. 155–163.

Van Donselaar, K.H., Peters, J., De Jong, A. and Broekmeulen, R.A.C.M. (2016), “Analysis and Forecasting of Demand during Promotions for Perishable Items”, International Journal of Production Economics, Elsevier, Vol. 172, pp. 65–75.

Duan, Q. and Liao, T.W. (2013), “A New Age-Based Replenishment Policy for Supply Chain Inventory Optimization of Highly Perishable Products”, International Journal of Production Economics, Elsevier, Vol. 145 No. 2, pp. 658–671.

Eisenhardt, K.M. (1989), “Building Theories from Case Study Research”, Academy of Management Review, Vol. 14 No. 4, pp. 532–550.

Eriksson, M., Strid, I. and Hansson, P.-A. (2014), “Waste of Organic and Conventional Meat and Dairy Products — A Case Study from Swedish Retail”, Resources, Conservation and Recycling, Elsevier B.V., Vol. 83, pp. 44–52.

Evans, J. (2016), "Effects of Food and Beverage Storage, Distribution, Display, and Consumer Handling on Shelf Life", in Subramaniam, P. (Ed.), The Stability and Shelf Life of Food, 2nd ed., Woodhead Publishing, Cambridge, pp. 107–140.

Fildes, R., Ma, S. and Kolassa, S. (2018), Retail Forecasting: Research and Practice, available at: https://doi.org/10.13140/RG.2.2.17747.22565.

Gneiting, T. (2011a), "Making and Evaluating Point Forecasts", Journal of the American Statistical Association, Vol. 106 No. 494, pp. 746–762.

Gneiting, T. (2011b), "Quantiles as Optimal Point Forecasts", International Journal of Forecasting, Elsevier B.V., Vol. 27 No. 2, pp. 197–207.

Goyal, S.K. and Giri, B.C. (2001), "Recent Trends in Modeling of Deteriorating Inventory", European Journal of Operational Research, Vol. 134 No. 1, pp. 1–16.

Granger, C.W.J. (1999), "Outline of Forecast Theory Using Generalized Cost Functions", Spanish Economic Review, Vol. 1 No. 2, pp. 161–173.

Granger, C.W.J. and Pesaran, M.H. (2000), "Economic and Statistical Measures of Forecast Accuracy", Journal of Forecasting, Vol. 19 No. 7, pp. 537–560.

Gruen, T.W., Corsten, D.S. and Bharadwaj, S. (2002), Retail Out-of-Stocks: A Worldwide Examination of Extent, Causes and Consumer Responses, Grocery Manufacturers of America, Washington.

Gružauskas, V., Gimžauskienė, E. and Navickas, V. (2019), "Forecasting Accuracy Influence on Logistics Clusters Activities: The Case of The Food Industry", Journal of Cleaner Production, Vol. 240, pp. 1–13.

Hanke, J.E. and Wichern, D.W. (2009), Business Forecasting, 9th ed., Pearson Prentice Hall, New Jersey.

He, Y., Li, D., Wu, S.J. and Shi, C. (2018), "Quality and Operations Management in Food Supply Chain", Journal of Food Quality, Vol. 2018, pp. 1–14.

Huber, J., Gossmann, A. and Stuckenschmidt, H. (2017), "Cluster-Based Hierarchical Demand Forecasting for Perishable Goods", Expert Systems with Applications, Elsevier Ltd, Vol. 76, pp. 140–151.

Hübner, A.H. (2011), "Retail Category Management Decision Support Systems", Lecture Notes in Economics and Mathematical Systems, 656th ed., Springer.

Hyndman, R., Anthanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-wild, M., Petropoulos, F., et al. (2019), "Package 'forecast'", Forecasting Functions for Time Series and Linear Models, 8.10., pp. 1–143.

Hyndman, R.J. (2006), "Another Look at Forecast-Accuracy Metrics for Intermittent Demand", Foresight: The International Journal of Applied Forecasting, No. 4, pp. 43–46.

Hyndman, R.J. and Khandakar, Y. (2008), "Automatic Time Series Forecasting: the forecast Package for R", Journal of Statistical Software, Vol. 27 No. 3, pp. 1–23.

Hyndman, R.J. and Koehler, A.B. (2006), "Another Look at Measures of Forecast Accuracy", International Journal of Forecasting, Vol. 22 No. 4, pp. 679–688.

Hyndman, R.J., Koehler, A.B., Ord, J.K. and Snyder, R.D. (2008), Forecasting with Exponential Smoothing, The State Space Aproach, Springer Series in

Statistics, Springer Berlin Heidelberg, Berlin, available at: https://doi.org/10.1007/978-3-540-71918-2.
Jacobsen, P.Ø. and Bjerre, M. (2015), Effekt & Effektivitet, Dansk Dagligvarehandel 2003-2013, Copenhagen Business School.
Kiil, K., Hvolby, H.H., Fraser, K., Dreyer, H. and Strandhagen, J.O. (2018), “Automatic Replenishment of Perishables in Grocery Retailing: The Value of Utilizing Remaining Shelf Life Information”, British Food Journal, Vol. 120 No. 9, pp. 2033–2046.
Kolassa, S. (2016), “Evaluating Predictive Count Data Distributions in Retail Sales Forecasting”, International Journal of Forecasting, Elsevier B.V., Vol. 32 No. 3, pp. 788–803.
Kolassa, S. (2020), “Why The ‘Best’ Point Forecast Depends on the Error or Accuracy Measure”, International Journal of Forecasting, Elsevier B.V., Vol. 36 No. 1, pp. 208–211.
Kolassa, S. and Schütz, W. (2007), “Advantages of the MAD/Mean Ratio over the MAPE”, Foresight: The International Journal of Applied Forecasting, No. 6, pp. 40–43.
Kourentzes, N., Barrow, D. and Petropoulos, F. (2019), “Another Look at Forecast Selection and Combination: Evidence from Forecast Pooling”, International Journal of Production Economics, Elsevier Ltd, Vol. 209 No. May 2018, pp. 226–235.
Kourentzes, N., Trapero, J.R. and Barrow, D.K. (2020), “Optimising Forecasting Models for Inventory Planning”, International Journal of Production Economics, Elsevier B.V., No. In press, pp. xx–xx.
Lee, T.-H. (2007), Loss Functions in Time Series Forecasting, White Paper, Riverside, available at: http://www.faculty.ucr.edu/~taelee/paper/lossfunctions.pdf.
Lowalekar, H. and Ravichandran, N. (2017), “A Combined Age-and-Stock Based Policy for Ordering Blood Units in Hospital Blood Banks”, International Transactions in Operational Research, Vol. 24 No. 6, pp. 1561–1586.
Mehdiyev, N., Enke, D., Fettke, P. and Loos, P. (2016), “Evaluating Forecasting Methods by Considering Different Accuracy Measures”, Procedia - Procedia Computer Science, The Author(s), Vol. 95, pp. 264–271.
Mena, C., Adenso-Diaz, B. and Yurt, O. (2011), “The Causes of Food Waste in the Supplier-Retailer Interface: Evidences from the UK and Spain”, Resources, Conservation and Recycling, Elsevier B.V., Vol. 55 No. 6, pp. 648–658.
de Moraes, C.C., de Oliveira Costa, F.H., Roberta Pereira, C., da Silva, A.L. and Delai, I. (2020), “Retail Food Waste: Mapping Causes and Reduction Practices”, Journal of Cleaner Production, Vol. 256, pp. 1–16.
Nahmias, S. and Pierskalla, W.P. (1973), “Optimal Ordering Policies For a Product That Perishes in Two Periods Subject to Stochastic Demand”, Naval Research Logistics Quarterly, Vol. 20 No. 2, pp. 207–229.
Nielsen. (2017), Western European FMCG Report Q4 2016.
Nielsen. (2018), Western European FMCG Report Q4 2017.

O'Hara-wild, M., Hyndman, R., Wang, E. and Caceres, G. (2020), "Package 'fable'", Forecasting Models for Tidy Time Series, 0.1.2., CRAN, pp. 1–57.

Petropoulos, F., Kourentzes, N., Nikolopoulos, K. and Siemsen, E. (2018), "Judgmental Selection of Forecasting Models", Journal of Operations Management, Elsevier, Vol. 60 No. May, pp. 34–46.

Priyadarshi, R., Panigrahi, A., Routroy, S. and Garg, G.K. (2019), "Demand Forecasting at Retail Stage for Selected Vegetables: A Performance Analysis", Journal of Modelling in Management, Vol. 14 No. 4, pp. 1042–1063.

Raafat, F. (1991), "Survey of Literature on Continuously Deteriorating Inventory Models", Journal of the Operational Research Society, Vol. 42 No. 1, pp. 27–37.

Ramos, P., Santos, N. and Rebelo, R. (2015), "Performance of State Space and ARIMA Models for Consumer Retail Sales Forecasting", Robotics and Computer-Integrated Manufacturing, Elsevier, Vol. 34, pp. 151–163.

Silver, E.A., Pyke, D.F. and Peterson, R. (1998), Inventory Management and Production Planning and Scheduling, John Wiley & Sons, Inc., Hoboken.

Steven Nahmias. (1982), "Perishable Inventory Theory : A Review", Operations Research, Vol. 30 No. 4, pp. 680–708.

Syntetos, A.A., Babai, M.Z., Lengu, D. and Altay, N. (2011), "Distributional Assumptions for Parametric Forecasting of Intermittent Demand", Service Parts Management, Demand Forecasting and Inventory Control, Vol. 53, Springer-Verlag, London, pp. 1689–1699.

Teller, C., Holweg, C., Reiner, G. and Kotzab, H. (2018), "Retail Store Operations and Food Waste", Journal of Cleaner Production, Elsevier Ltd, Vol. 185, pp. 981–997.

Trapero, J.R., Cardós, M. and Kourentzes, N. (2019a), "Quantile Forecast Optimal Combination to Enhance Safety Stock Estimation", International Journal of Forecasting, Elsevier B.V., Vol. 35 No. 1, pp. 239–250.

Trapero, J.R., Cardós, M. and Kourentzes, N. (2019b), "Empirical Safety Stock Estimation Based on Kernel and GARCH Models", Omega, Elsevier Ltd, Vol. 84, pp. 199–211.

Appendix 1: Performance measures

Table A1. Performance measures for all measures across all quantiles and products, wSLE scenario 1

			Inventory/demand (%)				Waste (%)				Fill-rate (%)				Lost sales (%)			
#	Measure	Model	0.80	0.85	0.90	0.95	0.80	0.85	0.90	0.95	0.80	0.85	0.90	0.95	0.80	0.85	0.90	0.95
1	RMSE	ARIMA	21.4	24.5	28.7	35.0	4.9	5.1	5.4	5.9	96.3	97.0	97.6	98.3	3.7	3.0	2.4	1.7
	wMAPE	Combi (ARIMA/ETS/Theta)	**18.4**	**21.2**	**25.4**	**32.2**	**4.6**	**4.8**	**5.1**	**5.6**	95.6	96.4	97.2	98.2	4.4	3.6	2.8	1.8
	wQL	Seasonal naive	27.3	32.2	38.5	48.7	5.0	5.4	6.1	7.1	**96.8**	**97.8**	**98.8**	**99.4**	**3.2**	**2.2**	**1.2**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	**18.4**	**21.2**	**25.4**	**32.2**	**4.6**	**4.8**	**5.1**	**5.6**	95.6	96.4	97.2	98.2	4.4	3.6	2.8	1.8
2	RMSE	Combi (ARIMA/ETS/Theta)	**17.0**	**21.2**	**26.0**	**34.4**	**0**	**0**	**0.3**	**0.6**	95.5	96.3	97.0	97.8	4.5	3.7	3.0	2.2
	wMAPE	Combi (ARIMA/ETS/Theta)	**17.0**	**21.2**	**26.0**	**34.4**	**0**	**0**	**0.3**	**0.6**	95.5	96.3	97.0	97.8	4.5	3.7	3.0	2.2
	wQL	Moving Average	24.3	28.8	34.7	43.4	1.0	1.2	1.5	2.0	**96.6**	**97.2**	**97.7**	**98.4**	**3.4**	**2.8**	**2.3**	**1.6**
	wSLE	Combi (ARIMA/ETS/Theta)	**17.0**	**21.2**	**26.0**	**34.4**	**0**	**0**	**0.3**	**0.6**	95.5	96.3	97.0	97.8	4.5	3.7	3.0	2.2
3	RMSE	Combi (ARIMA/ETS/Theta)	**9.9**	**10.9**	**13.9**	19.8	**0**	**0**	**0**	**0**	97.4	98.0	98.6	99.3	2.6	2.0	1.4	0.7
	wMAPE	Combi (ARIMA/ETS/Theta)	**9.9**	**10.9**	**13.9**	19.8	**0**	**0**	**0**	**0**	97.4	98.0	98.6	99.3	2.6	2.0	1.4	0.7
	wQL	Moving Average	15.8	18.8	22.8	28.7	**0**	**0**	**0**	**0**	**98.2**	**98.8**	**99.4**	**99.8**	**1.8**	**1.2**	**0.6**	**0.2**
	wSLE	ETS	10.9	12.9	14.9	**18.8**	**0**	**0**	**0**	**0**	97.9	98.3	98.8	99.2	2.1	1.7	1.2	0.8
4	RMSE	Theta	19.0	22.5	27.0	33.5	0.1	0.2	0.4	0.6	98.0	98.5	98.8	99.3	2.0	1.5	1.2	0.7
	wMAPE	Theta	19.0	22.5	27.0	33.5	0.1	0.2	0.4	0.6	98.0	98.5	98.8	99.3	2.0	1.5	1.2	0.7
	wQL	Moving Average	24.5	29.0	34.5	43.5	1.0	1.3	1.7	2.5	**99.0**	**99.5**	**99.8**	**100**	**1.0**	**0.5**	**0.2**	**0**
	wSLE	ARIMA	-	-	-	**26.5**	-	-	-	**0.2**	-	-	-	98.8	-	-	-	1.2
		Combi (ARIMA/ETS/Theta)	**14.0**	**17.5**	**20.5**	**-**	**0**	**0**	**0**	-	97.0	97.9	98.4	-	3.0	2.1	1.6	-
5	RMSE	ARIMA	11.4	13.3	15.5	19.3	**0**	**0**	**0**	**0**	98.1	98.3	98.6	98.8	1.9	1.7	1.4	1.2
	wMAPE	Combi (ARIMA/ETS/Theta)	**11.0**	**12.1**	**14.4**	**18.2**	**0**	**0**	**0**	**0**	98.0	98.2	98.4	98.7	2.0	1.8	1.6	1.3
	wQL	Moving Average	14.4	17.0	20.5	25.8	**0**	**0**	0.1	0.1	**98.3**	**98.7**	**99.1**	**99.4**	**1.7**	**1.3**	**0.9**	**0.6**
	wSLE	ARIMA	11.4	-	-	-	**0**	-	-	-	98.1	-	-	-	1.9	-	-	-
		Combi (ARIMA/ETS/Theta)	-	**12.1**	**14.4**	**18.2**	-	**0**	**0**	**0**	-	98.2	98.4	98.7	-	1.8	1.6	1.3
6	RMSE	Theta	**13.4**	16.4	19.4	23.9	**0**	**0**	**0**	**0**	**97.4**	**98.0**	**98.5**	**99.1**	**2.6**	**2.0**	**1.5**	**0.9**
	wMAPE	Theta	**13.4**	16.4	19.4	23.9	**0**	**0**	**0**	**0**	**97.4**	**98.0**	**98.5**	**99.1**	**2.6**	**2.0**	**1.5**	**0.9**
	wQL	Theta	**13.4**	16.4	19.4	23.9	**0**	**0**	**0**	**0**	**97.4**	**98.0**	**98.5**	**99.1**	**2.6**	**2.0**	**1.5**	**0.9**
	wSLE	Combi (ARIMA/ETS/Theta)	**-**	**13.4**	**16.4**	**19.4**	-	**0**	**0**	**0**	-	97.3	98.0	98.7	-	2.7	2.0	1.3
		Theta	**13.4**	**-**	**-**	**-**	**0**	-	-	-	**97.4**	-	-	-	**2.6**	-	-	-

			Inventory/demand (%)				Waste (%)				Fill-rate (%)				Lost sales (%)			
#	**Measure**	**Model**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**
7	RMSE	Combi (ARIMA/ETS/Theta)	**24.1**	**27.6**	**37.9**	51.7	**0**	**0**	**0**	**0**	97.1	97.9	98.9	**99.8**	2.9	2.1	1.1	**0.2**
	wMAPE	Combi (ARIMA/ETS/Theta)	**24.1**	**27.6**	**37.9**	51.7	**0**	**0**	**0**	**0**	97.1	97.9	98.9	**99.8**	2.9	2.1	1.1	**0.2**
	wQL	Theta	27.6	34.5	41.4	51.7	**0**	**0**	**0**	**0**	**97.5**	**98.4**	**99.1**	99.8	**2.5**	**1.6**	**0.9**	0.2
	wSLE	ARIMA	-	-	-	**48.3**	-	-	-	**0**	-	-	-	99.7	-	-	-	0.3
		Combi (ARIMA/ETS/Theta)	**24.1**	**27.6**	**37.9**	-	**0**	**0**	**0**	-	97.1	97.9	98.9	-	2.9	2.1	1.1	-
8	RMSE	Combi (ARIMA/ETS/Theta)	**9.5**	**11.1**	**14.0**	**20.8**	**0**	**0**	**0**	**0**	96.8	97.4	98.1	98.8	3.2	2.6	1.9	1.2
	wMAPE	Combi (ARIMA/ETS/Theta)	**9.5**	**11.1**	**14.0**	**20.8**	**0**	**0**	**0**	**0**	96.8	97.4	98.1	98.8	3.2	2.6	1.9	1.2
	wQL	Moving Average	15.0	17.3	20.4	25.4	**0**	**0**	**0**	**0**	**97.8**	**98.4**	**98.9**	**99.4**	**2.2**	**1.6**	**1.1**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	-	-	**14.0**	-	-	-	**0**	-	-	-	98.1	-	-	-	1.9	-
		ETS	-	13.0	-	19.9	-	**0**	-	**0**	-	97.8	-	98.7	-	2.2	-	1.3
		Naive	13.0	-	-	-	**0**	-	-	-	97.7	-	-	-	2.3	-	-	-
9	RMSE	Combi (ARIMA/ETS/Theta)	**16.3**	**20.2**	**25.0**	**30.3**	**0.5**	**0.7**	**0.8**	**1.1**	97.0	97.8	98.7	99.4	3.0	2.2	1.3	0.6
	wMAPE	Combi (ARIMA/ETS/Theta)	**16.3**	**20.2**	**25.0**	**30.3**	**0.5**	**0.7**	**0.8**	**1.1**	97.0	97.8	98.7	99.4	3.0	2.2	1.3	0.6
	wQL	Theta	19.7	23.1	27.4	34.6	0.9	1.1	1.3	1.7	**97.8**	**98.5**	**99.1**	**99.7**	**2.2**	**1.5**	**0.9**	**0.3**
	wSLE	Combi (ARIMA/ETS/Theta)	**16.3**	**20.2**	**25.0**	**30.3**	**0.5**	**0.7**	**0.8**	**1.1**	97.0	97.8	98.7	99.4	3.0	2.2	1.3	0.6
10	RMSE	Theta	7.3	8.5	10.9	13.9	**0**	**0**	**0**	**0**	97.7	98.1	98.5	99.0	2.3	1.9	1.5	1.0
	wMAPE	Theta	7.3	8.5	10.9	13.9	**0**	**0**	**0**	**0**	97.7	98.1	98.5	99.0	2.3	1.9	1.5	1.0
	wQL	ARIMA	7.9	9.1	11.5	14.5	**0**	**0**	**0**	0.1	**97.5**	**98.1**	**98.6**	**99.1**	**2.5**	**1.9**	**1.4**	**0.9**
	wSLE	Combi (ARIMA/ETS/Theta)	**5.5**	**6.7**	**8.5**	**12.1**	**0**	**0**	**0**	**0**	97.1	97.4	98.0	98.8	2.9	2.6	2.0	1.2
11	RMSE	Combi (ARIMA/ETS/Theta)	**16.8**	**19.7**	**24.5**	**32.2**	**0.5**	**0.6**	**0.8**	**1.4**	97.0	97.7	98.4	98.9	3.0	2.3	1.6	1.1
	wMAPE	Combi (ARIMA/ETS/Theta)	**16.8**	**19.7**	**24.5**	**32.2**	**0.5**	**0.6**	**0.8**	**1.4**	97.0	97.7	98.4	98.9	3.0	2.3	1.6	1.1
	wQL	ARIMA	22.1	26.0	30.8	38.9	1.3	1.5	1.8	2.7	**98.1**	**98.6**	**99.1**	**99.4**	**1.9**	**1.4**	**0.9**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	**16.8**	**19.7**	**24.5**	**32.2**	**0.5**	**0.6**	**0.8**	**1.4**	97.0	97.7	98.4	98.9	3.0	2.3	1.6	1.1
12	RMSE	Theta	**24.7**	30.3	**37.1**	48.3	**2.1**	2.7	**3.6**	5.1	**98.0**	**98.9**	**99.6**	**100**	**2.0**	**1.1**	**0.4**	**0**
	wMAPE	Theta	**24.7**	30.3	**37.1**	48.3	**2.1**	2.7	**3.6**	5.1	**98.0**	**98.9**	**99.6**	**100**	**2.0**	**1.1**	**0.4**	**0**
	wQL	Theta	**24.7**	30.3	**37.1**	48.3	**2.1**	2.7	**3.6**	5.1	**98.0**	**98.9**	**99.6**	**100**	**2.0**	**1.1**	**0.4**	**0**
	wSLE	Combi (ARIMA/ETS/Theta)	-	**25.8**	-	-	-	**2.5**	-	-	-	97.7	-	-	-	2.3	-	-
		ETS	-	-	-	**44.9**	-	-	-	**5.1**	-	-	-	99.2	-	-	-	0.8
		Theta	**24.7**	-	**37.1**	-	**2.1**	-	**3.6**	-	**98.0**	-	**99.6**	-	**2.0**	-	**0.4**	-

			Inventory/demand (%)				Waste (%)				Fill-rate (%)				Lost sales (%)			
#	**Measure**	**Model**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**	**0.80**	**0.85**	**0.90**	**0.95**
13	RMSE	Combi (ARIMA/ETS/Theta)	**13.3**	**15.5**	**19.5**	26.5	**0**	**0**	**0**	**0**	95.1	95.9	**96.9**	**97.9**	4.9	4.1	**3.1**	**2.1**
	wMAPE	Combi (ARIMA/ETS/Theta)	**13.3**	**15.5**	**19.5**	26.5	**0**	**0**	**0**	**0**	95.1	95.9	**96.9**	**97.9**	4.9	4.1	**3.1**	**2.1**
	wQL	Combi (ARIMA/ETS/Theta)	**13.3**	**15.5**	**19.5**	26.5	**0**	**0**	**0**	**0**	95.1	95.9	**96.9**	**97.9**	4.9	4.1	**3.1**	**2.1**
	wSLE	ARIMA	-	17.3	-	**24.8**	-	**0**	-	**0**	-	**96.2**	-	97.8	-	**3.8**	-	2.2
		Combi (ARIMA/ETS/Theta)	-	-	**19.5**	-	-	-	**0**	-	-	-	**96.9**	-	-	-	**3.1**	-
		Theta	17.7	-	-	-	**0**	-	-	-	**96.1**	-	-	-	**3.9**	-	-	-
14	RMSE	Combi (ARIMA/ETS/Theta)	**17.2**	**18.8**	**21.9**	**28.1**	**0.4**	**0.5**	**0.7**	**0.9**	95.7	96.7	97.3	98.0	4.3	3.3	2.7	2.0
	wMAPE	Combi (ARIMA/ETS/Theta)	**17.2**	**18.8**	**21.9**	**28.1**	**0.4**	**0.5**	**0.7**	**0.9**	95.7	96.7	97.3	98.0	4.3	3.3	2.7	2.0
	wQL	Moving Average	20.3	23.4	26.6	32.8	0.6	0.8	1.0	1.5	**96.3**	**97.1**	**97.9**	**98.6**	**3.7**	**2.9**	**2.1**	**1.4**
	wSLE	Combi (ARIMA/ETS/Theta)	**17.2**	**18.8**	**21.9**	**28.1**	**0.4**	**0.5**	**0.7**	**0.9**	95.7	96.7	97.3	98.0	4.3	3.3	2.7	2.0
15	RMSE	ARIMA	**20.8**	**25.0**	**29.2**	**35.4**	**0**	**0**	**0**	0.1	96.9	97.7	98.4	99.1	3.1	2.3	1.6	0.9
	wMAPE	ARIMA	**20.8**	**25.0**	**29.2**	**35.4**	**0**	**0**	**0**	0.1	96.9	97.7	98.4	99.1	3.1	2.3	1.6	0.9
	wQL	ETS	22.9	27.1	31.3	39.6	**0**	**0**	**0**	**0**	**97.2**	**98.0**	**98.8**	**99.4**	**2.8**	**2.0**	**1.2**	**0.6**
	wSLE	Combi (ARIMA/ETS/Theta)	-	-	**29.2**	37.5	-	-	**0**	**0**	-	-	98.3	99.2	-	-	1.7	0.8
		ETS	22.9	27.1	-	-	**0**	**0**	-	-	97.2	98.0	-	-	2.8	2.0	-	-
16	RMSE	Combi (ARIMA/ETS/Theta)	**17.4**	**19.6**	**26.1**	39.1	**0**	**0**	**0**	0.2	96.4	97.3	98.4	**99.3**	3.6	2.7	1.6	**0.7**
	wMAPE	Moving Average	21.7	23.9	30.4	37.0	**0**	**0**	**0**	0.1	97.5	98.1	98.6	99.1	2.5	1.9	1.4	0.9
	wQL	Theta	21.7	23.9	28.3	37.0	**0**	**0**	**0**	0.1	**97.2**	**97.9**	**98.6**	99.3	**2.8**	**2.1**	**1.4**	0.7
	wSLE	ARIMA	-	-	-	**34.8**	-	-	-	0.2	-	-	-	99.1	-	-	-	0.9
		Combi (ARIMA/ETS/Theta)	-	**19.6**	**26.1**	-	-	**0**	**0**	-	-	97.3	98.4	-	-	2.7	1.6	-
		Moving Average	21.7	-	-	-	**0**	-	-	-	97.5	-	-	-	2.5	-	-	-
17	RMSE	ARIMA	45.9	56.8	70.3	89.2	1.1	1.4	2.0	3.0	99.8	99.9	100	100	0.2	0.1	0	0
	wMAPE	ARIMA	45.9	56.8	70.3	89.2	1.1	1.4	2.0	3.0	99.8	99.9	100	100	0.2	0.1	0	0
	wQL	ETS	40.5	48.6	56.8	**70.3**	1.0	1.3	1.7	**2.3**	98.8	99.1	99.4	99.7	1.2	0.9	0.6	0.3
	wSLE	Combi (ARIMA/ETS/Theta)	**29.7**	**37.8**	**51.4**	-	**0.6**	**0.8**	**1.6**	-	98.0	99.2	99.7	-	2.0	0.8	0.3	-
		ETS	-	-	-	**70.3**	-	-	-	**2.3**	-	-	-	99.7	-	-	-	0.3

PAPER #7

Product Characteristics for Differentiated Replenishment Planning of Meat Products

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The PhD student defined the problem and proposed the structure and core scientific idea to solve it. The PhD student derived key-methodology, conducted case-study research and interviews, collected and analysed data, wrote the entire draft version of the paper, and re-vised it according to co-authors comments.

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ABSTRACT

Purpose: Meat products have different demands, shelf life and supply lead-time causing increased risk of waste and unavailability. As meat products are unfit for storing this raises the need for effective, efficient and differentiated replenishment planning throughout the supply chain. This, in particular for the wholesaler not having any control of the production of products but merely balancing diverging and converging product and information flows. Current planning frameworks mainly focus on production planning and sharing of information between producer and customer at product group level, rather than at wholesaler and individual product level. This article aims to provide a conceptual framework for differentiating the effective and efficient replenishment of meat products.

Design: Design of replenishment of meat products needs to be designed on product characteristic and not on at product group level, since meat product with a group may have different product characteristics due to e.g. shelf life and supply lead-time causing increased risk of waste and unavailability. We have developed a proposed a conceptual replenishment-planning model based on four main characteristics for particularly fresh meat product that supports differentiated planning and replenishment.

Findings: By taking into consideration four main characteristics for particularly fresh meat product, it is possible to identify how replenishment planning should differentiate in planning for different fresh meat products, at individual product level.

Value: This paper is amongst the first to address how to differentiate the planning of demand and supply of food products with short shelf life, at individual product level rather than group level, according unique product characteristics. It has value for researchers as it provides direction for future research to demonstrate how use of unique product characteristics may influence the ability to plan differentiated. For practitioners the values is in providing a framework for how to group deteriorating products reducing the risk of waste from deteriorated products.

1. Introduction

Grocery business consumers have ever-growing requirements for low price, constant availability, high quality (i.e. product freshness) and broad variety (Fernie et al., 2010; Jacobsen and Bjerre, 2015). Special for meat products, they have time-dependent scarcities in supply since their raw materials (i.e. animals) have different lifetimes when slaughtered, up to two years. Further, different meat products have dissimilar demand and (short) shelf life making them unfit for storing. Replenishing all products in the same undistinguishable way merely relying on stock building, causes increased risk of waste from expiration and profit loss (Mena et al., 2014). This makes the effective, efficient and differentiated planning of replenishment of products utmost important. In particular, since product availability influences customer loyalty (Kuhn and Sternbeck, 2013).

Current fresh food planning frameworks incorporating product characteristics (i.e. shelf life) mainly focus at manufacturers' production planning (Entrup, 2005; Romsdal, 2014) and, information sharing between supply chain stages for improving performance (Alftan et al., 2015; Kaipia, 2009; Kaipia et al., 2013) rather than wholesalers and directional guidance as how to operationalise the planning. Further, rather than individual product level current frameworks focus on the internal planning of product groups (Entrup, 2005; Ivert et al., 2015; Romsdal, 2014), differentiating via forecasting-, production strategy- and/or inventory management-oriented segmentation (van Kampen et al., 2012). This includes e.g. order characteristics (lead-time, shelf life, temperature etc.) and demand characteristics (seasonality, fluctuation, frequency etc.) (Boylan et al., 2008; Hanke and Wichern, 2009; Hübner et al., 2013; van Kampen et al., 2012; Williams, 1984).

This influences wholesaler' ability to effectively and efficiently plan negatively; first, since wholesaler does not have any control of the production of products (Hübner et al., 2013) but merely facilitates the converging and diverging information and product flow through replenishment. Second, since the products are different in terms of supply lead-time, demand and shelf life. Third, since deteriorating, the products are unsuitable for longer time storing requiring limited time from order dispatch to order arrival. One replenishment cycle governs the time from an order is placed (or production is initiated) until the order has arrived (or completed) (Nahmias, 2005; Silver et al., 1998). Since no storing, and, between 40 days to more than two years' production time (i.e. growth-/life-time) of animals, it is relevant to investigate how replenishments should be planned (and differentiated) through product level-based classification. By taking into consideration four main characteristics for particularly fresh meat products, it is possible to identify how the replenishment planning should differentiate. Focus is on fresh meat products with up to 14 days shelf life. The following presents theoretical background, followed by investigation of four key-characteristics (forecasting and demand behaviour, supply lead-time and growth time, degradation and shelf life, and, frequency and intermittent demand), presentation of conceptual framework, and finally discussion and conclusion.

2. Theoretical Background

A main goal when balancing demand with supply throughout the supply chain is to share information enabling the forecasting of future demand, causing timely replenishments which allow demand to be met instantly when occurring – effectively and efficiently (Hübner et al., 2013; Lambert, 2008). Where traditional replenishment (on non-deteriorating products) relies on building inventories to meet demand and withstand fluctuations, based on a trade-off between inventory costs and service level to customer, deteriorating products needs a trade-off between waste (since inventory turns into waste due to short shelf life) and service level.

When determining the quantity to replenish, numerous models exist to accommodate an optimized order dispatching for deteriorating products (Bakker et al., 2012; Goyal and Giri, 2001; Raafat, 1991), relying on the newsvendor problem (Silver et al., 1998). However, apart from merely determining the order size, efficiency is gained in higher degree when choosing optimum order rules – i.e. when to initiate the ordering of the products (Nahmias, 2005; Silver et al., 1998). The quantity to order may be either fixed for all replenishments (Q), or, variable and represent the required amount to reach a certain level (S). Time for order may similarly be either fixed interval (R), or, variable interval (s) – that is when inventory level drops below a predefined level (i.e. re-order point (ROP)). However, Wensing (2011) and Silver, et al. (1998) additionally highlight the situation of way of reviewing inventory levels. Adding more complexity, time-point for reviewing inventory levels may either be at fixed times (R), or, continuous (R=0) – that is when $R \rightarrow 0$. In total five policies are possible: (s, S) and (R, s, S) suitable for A-times, and, (s, Q), (R, s, Q) and (R, S) suitable for B-items (Silver et al., 1998). However, meat products requires a different approach. Since degrading with constantly increasing chance of expiring (causing waste) and no longer storing of products is desirable, meat products must be evaluated against waste costs and the actual deterioration of the product instead.

Since different products behave differently through time, this raises the need for appropriate classification of meat products securing the relevant differentiation. Following van Kampen et al. (2012) the context (i.e. fresh meat products) and aim (i.e. planning of replenishments) of the classification influences the choice of characteristics. Given the limitations in currently classification methods, interest thus lies in investigating the different characteristics for fresh meat products and their inter-relations. As for the number of characteristics to choose, van Kampen, et al.'s (2012) note that no consensus seem to exist and in general up to ten characteristics are used – however, without clear argumentation for choosing this number.

Meat products constantly deteriorates through time, and are highly volatile to factors alike seasons and weather, leaving them with a latent uncertainty and particularly high variation in demand. Four characteristics are found relevant for grouping the meat products. Since meat products deteriorate, storing for longer time is undesirable, meaning the ability to forecast with high precision is important, making demand variation the first parameter. Connected to this is the shelf life, ranging from only few days to 14 days, requiring different tolerance and sensitivity to storing (e.g. fish with maximum storing of one day versus grounded beef with a few days) – thus also overestimation and oversupply. Thirdly is supply lead time, that is, the time it takes from an animal is born until it is ready for slaughtering, ranging from 40 days (i.e. chicken) to more than two years (i.e. cow). The last characteristic is (customer) ordering frequency, since meat products may not have demand constantly due to days without demand, closing days, holidays, additional opening, etc. This influences the planning and forecasting methods using lag indicators. The parameters are explored in greater depth, in the following.

2.1. Variation in Demand and Forecasting

Forecast drives planning of demand (Hübner et al., 2013) and consumers' purchases in shops set the supply chain in motion. This makes the ability to forecast as accurate as possible to efficiently and effectively replenish products and fulfill downstream demand a first step in providing customer service (Lambert, 2008). As consolidator in the supply chain, wholesaler must be able to interpret and plan efficiently and effectively to expected level of demand (Kuhn and Sternbeck, 2013), "to be more proactive to anticipated demand and more reactive to unanticipated demand" (Lambert, 2008, p. 87), in turn influencing implications when moving up the supply chain (i.e. reducing bullwhip effect) (Chen et al., 2000).

Improvement of forecasting is a "key factor for improving supply chain operations in the food industry supply chain" (Adebanjo, 2009) to create a cost-effective supply chain. Apart from time-horizon to forecast, the prediction of future demand relies in significant degree on choice of forecasting method, which in turn ultimately relies on demand pattern (Hanke and Wichern, 2009).

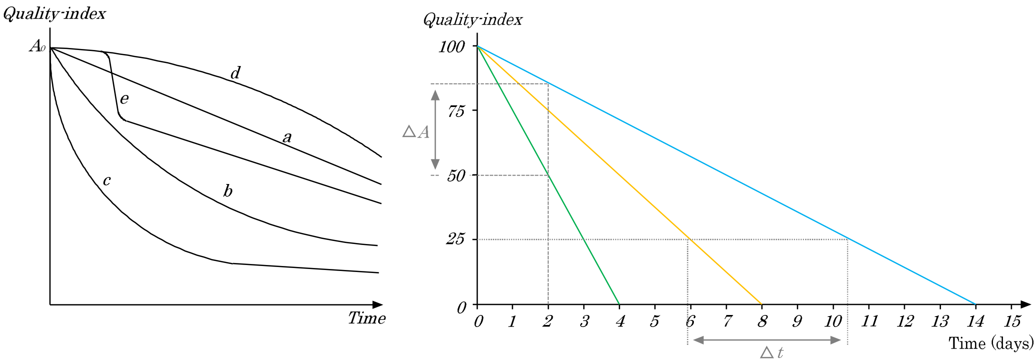
Demand across all products does not behave in same way (Adebanjo, 2009), and frequently ordered product's demand behaviour may be characterized according to four different types of pattern: horizontal, trend, seasonal and cyclical (Hanke and Wichern, 2009). Adebanjo (2009) classifies products based on product type, in regards of required effort in determination of demand (steady, seasonal or promotional), each with different requirements and level of supply chain collaboration, ranging from low to high. He further claims that a diversified approach for predicting future demand leads to significant savings and increased supply chain performance. Additional to this classification of products, with great impact on the accuracy of forecasting, is the variation in demand. The more stable demand the greater reliability and less attention required when forecasting, thus the greater suitability for automated forecasting. Similarly, the less stable demand, the less reliability and greater need to attention when forecasting. To evaluate this, the coefficient of variation (CV) is suitable. CV is a measure of spread describing the variability relative to the mean in a unit less manner. This allows the different products to be compared, and thus found one dimension for grouping products in terms of differentiated replenishment planning.

2.2. Shelf Life of Fresh Food Products

Since fresh meat products immediately (after production) degrades in quality constantly, interest is in incorporating the shelf life when planning. Shelf life is defined in different ways: practical storage life (PSL), high-quality life or noticeable difference (usually used for fruits and vegetables). For the purpose of this article PSL is suggested, and is defined by IIR (International Institute of Refrigeration) as "the period of storage at that temperature during which the product retains its characteristics properties and remains both suitable and acceptable for consumption or the intended purpose" (Evans, 2016). Though seeming similar to e.g. frozen and chilled products, meat products remain more complicated since up to 14 days shelf life from production. Whereas chilled food, and in particular frozen, products are fit for up to several months (even years) of storing, fresh meat products have down to few days' shelf life, e.g. sushi, grounded fish and Boeuf bourguignon with shelf life of five days from production. Planning replenishment relying on identical stock building approach for all products, not consideration the different products' deterioration, causes increased risk of waste from expiration and profit loss.

The product's shelf life (or food quality) follows the quality index' kinetic function. The loss in quality through time ($\partial A/\partial t$) is essentially described as $-\frac{\partial A}{\partial t} = kA^n$, where A is quality index value, k is rate constant (dependent on temperature, product and packaging characteristics), and n is the "reaction order which defines whether the rate of change is dependent on the amount of A present" and the shape of the deterioration curve if environmental factors are constant (Fu and Labuza, 1997, p. 4). The curves may have different shapes (see left graph in Figure 1): linear (a), exponential (b), hyperbolic (c), quadratic (d) or complex (e) function (Fu and Labuza, 1997).

Figure 1: Deterioration Curves (left) from Fu and Labuza (1997), with an Example of Linear Deterioration Curve for Different Products in Relation to Quality and Time (right)



The right graph in Figure 1 illustrates the relationship between quality-index and time; for reasons of simplicity and illustration, the following assumes a linear deterioration curve (that is $n = 0$) for three products. As meat products start degradation immediately after production, any time-period until delivery is critical and influences the level of quality in the product. Assuming A_0 is the immediate moment after production (quality level = 100), two days influences the product significantly, with decrease in quality index of approximately 30 (see dotted lines ΔA). Similarly, when looking at specific quality level, there is more than four days in difference before reaching e.g. quality level 25 for two products (see dotted lines for Δt). For order dispatching, this means a trade-off must be met between cost-based quantity and quality-based quantity. Saying this, a purely economic order based model assume products have indefinite amount of storage lifetime. However, because of the deterioration, a quality-based takes this into consideration and thus per se suggests lower amounts to purchase when planning. Consequently, more orders will be dispatched to supplier in order to fulfil same demand, in turn causing increasing ordering costs. To overcome this Bakker, et al. (2012) and Goyal & Giri (2001) provide literature overview of different inventory ordering models taking this into consideration. Given the scope of this article, further attention is delimited.

2.3. Supply Lead Time of Animals

Related to forecasting is the supply lead time, that is the time it takes to grow the raw material (i.e. animal) before it is ready for the given meat product. Planning replenishment of meat products is influenced by latent scarcity (in their raw materials) from a certain point in time. From the time point an amount of animals is given birth and starts to grow, no additional amount of raw materials is available per se. This, since meat products are not subject for longer term storing, contrary to other types of products. Also, different animals have different time windows for being acceptable for use in meat production, to ensure uniform product quality and avoidance of damages to the animals (e.g. if living for too long time chickens grow too big and break their feet). If exceeding these time-windows the animals become unfit for production, i.e. waste. Table 1 shows the different animal-groups' growth time (until ready for slaughtering) and time-window for being acceptable for slaughtering, following Danish Agriculture and Food Council.

Table 1: Age/Size of Animals Slaughtering & Catching Time

Chicken	Pork	Beef	Fish, examples
≈ 40 days	≈ 5-6 months (90-105 kilos)	<10 months (veal) 10-24 months (young cattle) >24 months (cow-beef)	>40-60* cm (salmon) >25-27* cm (flounder) >30-35* cm (cod)

**depends on the catching-area (North Sea, Baltic Sea, Kattegat, etc.) and sea-type (salt- or freshwater)*

Chicken and pork have the shortest life times, with respectively 40 days and five to six months (depending on a weight between 90 and 105 kilograms). Consequently, these groups also have the shortest forecasting horizons compared to the other product groups. However, they have a time-window of acceptance for production of only few days and one month, respectively, before causing waste, in turn, requiring a comparable greater level of attention when planning. Beef has a stepwise evolvement without any further delimitating time-window. Split into three types of beef, then, if the animals become too old for being classified as veal (more than 10 months), they merely re-classify and change type to young cattle. Similarly, if becoming too old for this classification (more than 24 months), they change type to cow-beef where "the-bigger-the-merrier"-principle applies. Fish are influenced by factors alike e.g. nature, climate and nutrition available in the water, and thus caught and slaughtered according to size instead of age, with no predetermined amount of growth time. Instead, "the-bigger-the-merrier"-principle applies, meaning, the bigger fish means greater value (i.e. revenue).

These differences influence not only the preciseness in forecasting but also the type of forecasting (long term versus short term forecasting), and the attention and the effort needed in planning replenishment. Moreover, where chickens' replenishment cycle is short and influences only short-term planning (< 6 months), pork is on the border of influencing medium-term planning (6-12 months) and beef influences long-term planning (>12 months) (Hübner et al., 2013). Hence, meat products' replenishments require life-time-based differentiation in planning, sharing of demand information (with differentiated influence of replenishment on demand and supply planning) and level of collaboration.

2.4. Ordering Frequency of Products

In regards of frequency, van Kampen, et al. (2012) find one particular popular criterion: order frequency, representing the frequency a products is ordered e.g. annually. By using this in replenishment planning, it takes into consideration whether a product is ordered often or not. Specifically for meat products, this is of interest due to the deterioration. The less frequency, the less time per period the product is ordered, hence the greater attention required when ordering. Common forecasting techniques assume a constant demand (i.e. demand in each inventory period) – however, not all products face such constant demand, e.g. campaign products, seasonal products and low selling products. This hence influences replenishment planning in great degree – including the forecasting. E.g., if applying common exponentially smoothing forecasting techniques in planning, greater weight will be attained latest observation – which may be zero due to the demand pattern. In turn, this will interrupt the forecast and cause negative influence and increased risk of either over- or understocking. Hence, as demand patterns are not identical for all products and differentiate, Eaves & Kingsman (2004, p. 432) highlight that ”it is useful to classify line items according to their observed demand pattern and perhaps use alternative methods when demand is intermittent or slow moving”.

The products with infrequent demand, Williams (1984) groups as either smooth, slow moving or intermittent. Boylan, et al. (2008) state in their framework that a non-normal product's demand can be intermittent, slow moving, erratic, lumpy or clumped. Determining what is non-normal demand, Eaves & Kingsman (2004, p. 432) note, "with intermittent items the observed demand during many periods is zero interspersed by occasional periods with irregular nonzero demand". Boylan, et al. (2008, p. 474) further point out that "infrequent demand occurrences or irregular demand sizes, when demand occurs, do not allow lead time to be represented by the normal distribution". Varghese & Rossetti (2008) highlight different definitions of intermittent demand, hereunder e.g. as "many time periods with zero demand", series with at least 30% of zero demand" and "series with less than or equal to 60-70% non-zero demand".

3. Conceptual Replenishment Planning Model

Having four characteristics, a four-dimensional space is required and here many simple classification techniques falls short. Each characteristic is divided into up to three groups (low/short, medium or long/high), and represent in combination the suggested conceptual model for planning demand and supply of fresh meat products, see Table 2.

Table 2: Replenishment Guidelines for Product Classification

	low	**medium**	**high**
Coefficient of variation	The product has stable and predictable demand, where reliable forecast is possible. Little attention is needed for forecast, and product is subject for possible automation. Relatively lower SS and ROP is required.	The product has less stable demand and less reliable forecast with significant forecast errors. Forecast require post-evaluation with possible adjustments. Depending on variation, ROPs and SS need re-evaluation periodically.	The product has instable demand, significant fluctuations and unreliable forecast with very significant errors. Forecast require significant attention and constant monitoring of demand. Manage products, SS and ROPs closely and adjust accordingly.
	slow	**medium**	**fast**
Degrading speed	The product has long shelf life (i.e. PSL) up to several days, even weeks. When ordering use EOQ-based order size calculation.	The product has mixed shelf life (i.e. PSL) ranging from few days to several days. When ordering use either quality- or EOQ-based order size calculation.	The product has short shelf life (i.e. PSL) up to only few days. When ordering use quality-based order size calculation, and, manage and monitor inventory level closely.
	short	**medium**	**long**
Supply lead-time	The product has short supply lead-time with fast response time from supplier and thus relatively lower latent uncertainty. Forecast daily and initiate replenishments accordingly. Send forecasts to internal operations and supplier.	The product has medium supply lead-time with medium response time from supplier and relatively higher latent uncertainty. Initiate replenishments on daily basis as needed, and forecast medium-term sales with regular review and adjustment. Forecast may be input to medium-term other planning aspects, may thus be forwarded internally – and externally (in case of campaigns).	The product has long supply lead-time with low response time from supplier and thus high latent uncertainty. Initiate replenishments on daily basis as needed, and forecast long-term sales, with frequent review and adjustment – with principle of general overestimation (due to life-time window). Forecast may be input to other medium-/long-term planning aspects, and may this be forwarded internally.
	high	**medium**	**low**
Order frequency	The product is ordered very frequently (if not each day), and has relatively lower risk for long storage. Given a higher turnover, less atten-tion is needed and product may be subject for automatic order generation (or automotive replenishment).	The product is ordered infrequently and possibly a cyclical product. Manage and monitor products closely, analyse and understand demand and adjust SSs and ROPs periodically	The product is ordered rarely (possibly seasonal), has lower turnover and thus faces a relatively higher risk of long storage time. Manage and monitor products closely, analyse and understand demand and adjust SSs and ROPs accordingly.

For coefficient of variation, high value mean less reliable forecast and thus high attention required to RP&C. On the other hand, low valuation means high reliability in forecast and thus requiring less attention to the planning. In fact, the lower valuation, the greater potential has the product of having automated replenishment. For supply lead-time, long means higher uncertainty in planning and additionally greater influence on quality degradation of the products, qua the accordingly higher inventory levels. Low lead-time indicates less uncertainty in planning and less influence on quality level, making these products' replenishment very flexible. In particular, supply lead-time is influenced animals' lifetime, and vary not only within each animal's lifetime (pork may deviate up to one month since 5-6 months' lifetime), but also latent between different animals (chicken has lifetime of 40 days where e.g. fish has unknown lifetime). For deterioration, the higher level the more attention required and the greater trade-off between costs and quality. Deteriorating very fast, inventory levels are maintained with greater focus. On the contrary, low level allow a less requiring management. The lower degrading speed, the more tolerance for economic order quantity-based management. Finally, for order frequency high valuation means very frequent request of product. For planning this influence the decision making in regards of quality. The higher order frequency, the less influence has the degradation. If a product has high frequency (ordered often) – inventories are influenced through lower levels and thus lower risk of obsolescence. Hence, the lower frequency the greater attention to forecast and planning (recall non-normal demand patterns). When grouping e.g. demand variation as either high, medium or low different authors point out that boundaries between each of the categories is essentially a management decision (Eaves and Kingsman, 2004; Williams, 1984). Therefore, the grouping is not quantitatively shown (with cut-off values), but rather illustratively suggested for the different conceptual groups of products.

Table 3: Example of Values for Classification from Four Different Products

	Grounded beef 8-12%	**Sushi-box 9pcs.**	**Chicken breast w/ barbeque**	**Pork filet w/ tomatoes & oregano**
Shelf life	8 days	5 days	11 days	14 days
Supply lead time	+ 2 years	up to 1 year	40 days	5-6 months
Coefficient of variation[1]	0.618	0.137	1.920	1.090
Frequency	1.000	0.958	1.000	0.247

[1]Coefficient of variance is based on sample data, and thus an unbiased estimator for sample size *n* is used.

As example four different products are classified, see Table 3. Compared to one another, replenishment planning of grounded beef has influence on medium- and long-term planning, and requires long-term forecasting. Since constant demand and relatively low coefficient of variation, with medium shelf life, it may be subject for automated replenishment with manual adjustment for campaigns and seasonal fluctuation. Sushi box requires, although low coefficient of variation, close monitoring since relatively longer supply lead time and low shelf life with no constant demand. Chicken breast has constant demand, with medium/long shelf life and relatively short supply lead-time, hence forecasting and replenishment may be automated, despite the high fluctuation. Hence, check for campaign and seasonal fluctuation. Pork filet requires closest attention during replenishment planning, since very infrequent demand (despite long shelf life) and medium/longer supply lead-time.

4. Conclusion & Further Research

The background for the study is the increasing focus on low price, wide assortment, high quality in and constant availability of fresh food products, raising the need for low cost, differentiated, efficient and effective planning. This to avoid reduction in profit base from wasted (i.e. deteriorated) products. Where current frameworks for planning take stance within certain level of uniform approach, the unique and diversified characteristics of each products seem to be overlooked. Although there is increased focus on green and sustainable supply chain performance, the risk of facing waste from inefficient and ineffective operations and decision making (i.e. food waste) remains. Further research is proposed to govern testing of the framework across a range of meat products with short shelf life range to determine its influence on planning of demand and supply, as well as the influence on performance in planning. Further, it is suggested to test the framework across a broader range of products with short-to-medium(-to-long)-term shelf life such as chilled and frozen food products, to test its general applicability for other products.

5. References

Adebanjo, D., 2009. Understanding Demand Management Challenges in Intermediary Food Trading: A Case Study. Supply Chain Manag. An Int. J. 14, 224–233.

Alftan, A., Kaipia, R., Loikkanen, L., Sepns, K., 2015. Centralised Grocery Supply Chain Planning: Improved Exception Management. Int. J. Phys. Distrib. Logist. Manag. 45, 237–259.

Bakker, M., Riezebos, J., Teunter, R.H., 2012. Review of Inventory Systems with Deterioration Since 2001. Eur. J. Oper. Res. 221, 275–284.

Boylan, J., Syntetos, A., Karakostas, G., 2008. Classification for Forecasting and Stock Control: A Case Study. J. Oper. Res. Soc. 59, 473–481.

Chen, F., Drezner, Z., Ryan, J.K., Simchi-levi, D., Chen, F., Drezner, Z., Ryan, J.K., 2000. Quantifying the Bullwhip Effect in a Simple Supply Chain: The Impact of Forecasting, Lead Times, and Information. Manage. Sci. 46, 436–443.

Eaves, A.H.C., Kingsman, B.G., 2004. Forecasting for the Ordering and Stock-Holding of Spare Parts. J. Oper. Res. Soc. 55, 431–437.

Entrup, M.L., 2005. Advanced Planning in Fresh Food Industries, Integrating Shelf Life into Production Planning. Physica-Verlag Heidelberg, Berlin.

Evans, J., 2016. Effects of Food and Beverage Storage, Distribution, Display, and

Consumer Handling on Shelf Life. In: P. Subramaniam (Ed.), The Stability and Shelf Life of Food. Woodhead Publishing, Cambridge, pp. 107–140.

Fernie, J., Sparks, L., McKinnon, A.C., 2010. Retail Logistics in the UK: Past, Present and Future. Int. J. Retail Distrib. Manag. 38, 894–914.

Fu, B., Labuza, T.P., 1997. Shelf Life Testing: Procedures and Prediction Methods for Frozen Foods. In: Erickson, M.C., Hung, Y.-C. (Eds.), Quality in Frozen Food. Chapman & Hall, pp. 377–415.

Goyal, S.K., Giri, B.C., 2001. Recent Trends in Modeling of Deteriorating Inventory. Eur. J. Oper. Res. 134, 1–16.

Hanke, J.E., Wichern, D.W., 2009. Business Forecasting, 9th ed. Pearson Prentice Hall, New Jersey.

Hübner, A.H., Kuhn, H., Sternbeck, M.G., 2013. Demand and Supply Chain Planning in Grocery Retail: an Operations Planning Framework. Int. J. Retail Distrib. Manag. 41, 512–530.

Ivert, L.K., Dukovska-Popovska, I., Kaipia, R., Fredriksson, A., Dreyer, H.C., Johansson, M.I., Chabada, L., Damgaard, C.M., Tuomikangas, N., 2015. Sales and Operations Planning: Responding to the Needs of Industrial Food Producers. Prod. Plan. Control 26, 280–295.

Jacobsen, P.Ø., Bjerre, M., 2015. Effekt & Effektivitet, Dansk Dagligvarehandel 2003-2013. Copenhagen Business School.

Kaipia, R., 2009. Coordinating Material and Information Flows with Supply Chain Planning. Int. J. Logist. Manag. 20, 144–162.

Kaipia, R., Dukovska-Popovska, I., Loikkanen, L., 2013. Creating Sustainable Fresh Food Supply Chains through Waste Reduction. Int. J. Phys. Distrib. Logist. Manag. 43, 262–276.

Kuhn, H., Sternbeck, M.G., 2013. Integrative retail logistics: An exploratory study. Oper. Manag. Res. 6, 2–18.

Lambert, D.M., 2008. Supply Chain Management - Processes, Partnership, Performance. Supply Chain Management Institute, Sarasota.

Mena, C., Terry, L.A., Williams, A., Ellram, L., 2014. Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector. Int. J. Prod. Econ. 152, 144–158.

Nahmias, S., 2005. Production & Operations Analysis. McGraw-Hill, New York.

Raafat, F., 1991. Survey of Literature on Continuously Deteriorating Inventory Models. J. Oper. Res. Soc. 42, 27–37.

Romsdal, A., 2014. Differentiated Production Planning and Control in Food Supply Chains.

Silver, E.A., Pyke, D.F., Peterson, R., 1998. Inventory Management and Production Planning and Scheduling. John Wiley & Sons, Inc., Hoboken.

van Kampen, T.J., Akkerman, R., van Donk, D.P., 2012. SKU Classification: a Literature Review and Conceptual Framework. Int. J. Oper. Prod. Manag. 32, 850–876.

Varghese, V., Rossetti, M., 2008. A Classification Approach for Selecting Forecasting Techniques for Intermittent Demand. Ind. Eng. Res. Conf. 1, 863–868.

Wensing, T., 2011. Periodic Review Inventory Systems. Springer Berlin Heidelberg, New York.
Williams, T.M., 1984. Stock Control with Sporadic and Slow-Moving Demand. J. Oper. Res. Soc. 35, 939–948.

PAPER #8

Managing Perishable Multi-Product Inventory with Supplier Fill-Rate, Price Reduction and Substitution

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The PhD student defined the problem and proposed the structure and core scientific idea to solve it. The PhD student derived key-methodology, conducted case-study research and interviews, collected and analysed data, wrote the entire draft version of the paper, and re-vised it according to co-authors comments.

Managing Perishable Multi-Product Inventory with Supplier Fill-Rate, Price Reduction and Substitution

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Abstract. Order-sizing in replenishment planning and control for perishable products is studied in grocery retail context. There is a need for age-based policies that consider multiple products, the impact from price reduction (due to close-to-expiration), and product substitution in order to reduce waste, increase availability and improve freshness. This study develops a theoretical extension to known EWA-models considering positive and/or negative interdependence in substitution between products, impact from price reduction and expired products, as well as the inventory impact from other products safety stocks.

Keywords: inventory control · shelf-life · perishable · substitution

1. Introduction

The grocery market faces ever-growing requirements to product availability and freshness [1]. Majority of consumers often feel disappointed with fresh food products' (FFP) availability and freshness when grocery shopping [2]. The FFPs have down to few days shelf-life with high waste-levels when comparing with other product types [3]. Increasing remaining shelf-life one day causes improved freshness, availability and waste [4].

Grocery demand is stochastic and non-stationary over the week with high sales in weekends [5]. This, as well as the increased focus on food waste and use of automated replenishment systems across product assortments [6], put high requirements on the FFP replenishment planning and control at wholesaler and retail store. Different heuristics have been suggested to manage perishables in automated replenishment systems when considering the product's remaining shelf-life [5, 7–9]. However, they do not reflect certain real-life situations. Grocery wholesaler/retailer faces different product characteristics that influence the order-size decision-making of FFPs:

1. Price-reduction: if "FFP A" is close to expiration, its price is reduced (in rounds) to minimize waste. The demand for the price reduced "FFP A"

depends on the reduction i.e. price elasticity, which influences the available inventory in different degrees.

2. Order fill-rate: FFPs to be delivered in the future, not yet in transit, may be influenced by (suddenly) reduced fill-rate due to factors such as e.g. sudden raw-material unavailability. This influences the safety stock, hence the ability to withstand variation in demand level, thus order-sizing of FFPs.
3. Substitution demand: if "FFP A" is out-of-stock it may be substituted with "FFP B", causing extraordinary substitution demand on "FFP B" – and vice versa, depending on the products' positive and/or negative interdependence [10].
4. Substitution inventory: FFPs have asymmetrical financial losses[17] with increased food waste focus. Therefore, instead of buying too many "FFP B" (due to e.g. minimum order quantities) which causes excess inventory, hence increased risk of waste from expiration, the available inventory from substituting "FFP A" may satisfy "FFP B"'s demand, thereby mitigate risk.

By investigating current heuristics for perishable (automated) replenishment planning and control, it is possible to see how substitution, price reduction and reduced fill-rate in future orders may be included in the decision-making. The following presents the background, the developed multi-product EWA_{3SL}, and ends with conclusion.

1.1. Inventory Control for Perishable Products

Numerous inventory control systems have been introduced for perishable products with fixed or random shelf-life and fixed or continuous review period, modelling deterministic or stochastic demand [11–15]. Fixed shelf-life is a known and deterministic time period where a product deteriorates (e.g. fresh meat, dairy and chilled food products), while random shelf-life is a probabilistic time period where a product deteriorates (e.g. fruits and vegetables). Recent studies primarily concern single items assuming deterministic demand, mainly focusing on pricing and lot-sizing or multi-echelon – and shortages are considered through back-ordering [14]. For products with particular short shelf-life, i.e. one day, the news-boy problem is considered appropriate [15]. Extended versions covering two periods with stochastic demand are suggested by e.g. [16].

For products with up to few weeks shelf-life such as fresh meat and dairy products the OIR policy [8], age-and-stock-based (CASB) policy [9] and the EWA policy [5] are considered. The old inventory ratio (OIR) policy is a two-step policy minimizing the expected number of outdated products given a predetermined allowance for out-of-stock. The inventory position is raised to order-up-to level, and then, if the ratio between old (i.e. outdated) and total inventory position on hand is larger than a specified threshold, an additional order quantity corresponding to the number of outdated products is ordered. Simulation results for blood products show significant reduction in outdated

[17] Too few products mean lost sales i.e. profit – too many means lost purchase and handling costs.

products (19,6% to 1,04%) while keeping sufficiently high fill-rate [8]. A variation of the OIR is the CASB policy with a continuous review [9]. An order quantity is suggested either when total inventory position drops to a specified number of products (re-order point) or when the oldest batch has aged t units of time; whichever comes first [9]. Since the review is continuous, the required safety stock is lower [15].

The EWA policy considers the estimated number of products to outdate within the review period. Based on [15] the EWA batches store orders according to case sizes with positive lead-times and weekly time-varying demand, as known in the grocery industry [5]. They obtain 17,7% increase in inventory availability and 3,4% waste reduction for products with 4-7 days shelf-life when comparing to stock-based policy. [7] extends the EWA to EWASS considering the size of safety stock relative to the expected number of products outdated within the review period. They simulate grocery products with short shelf-life and compare with a stock-based policy and obtain improved results on waste reduction compared to [5]: 10,3% increase in inventory availability and 10,7% waste reduction. The latest EWASS suggested by [7] is in equation (1)-(2):

If ,

$$\mathrm{I_t} - \sum_{\mathrm{i=t+1}}^{\mathrm{t+R+L-1}} \hat{\mathrm{O}}_{\mathrm{i}} < \sum_{\mathrm{i=t+1}}^{\mathrm{t+R+L}} \mathrm{E[D]} + \mathrm{SS} \tag{1}$$

then,

$$\mathrm{Q_t} = \begin{cases} \max\left(\dfrac{\sum_{i=t+1}^{t+R+L} E[D] + \sum_{i=t+1}^{t+R+L-1} \hat{\mathrm{O}}_i - I_t}{B}, 0\right) & \text{if, SS} < \displaystyle\sum_{\mathrm{i=t+1}}^{\mathrm{t+R+L-1}} \hat{\mathrm{O}}_{\mathrm{i}} \\ \max\left(\dfrac{\sum_{i=t+1}^{t+R+L} E[D] + SS - I_t}{B}, 0\right) & \text{if, SS} \geq \displaystyle\sum_{\mathrm{i=t+1}}^{\mathrm{t+R+L-1}} \hat{\mathrm{O}}_{\mathrm{i}} \end{cases} \tag{2}$$

$E[D]$ = expected product demand within review time
I_t = inventory position of product at time t
$\hat{\mathrm{O}}_i$ = estimated number of products to expire within review time
SS = safety stock for product

Although $\mathrm{EWA_{SS}}$ includes the size of safety stock relative to the estimated number of products that will outdate, it is for a single product as with EWA, OIR and CASB. Since including only one product, they do not consider the additional demand created from other products which are sold out and out-of-stock (i.e. substitutions demand). Further, they do not include the impact from when selling product close to expiration at reduced price.

1.2. Product Characteristics

Different planning environment characteristics influence FFPs [17]. In this study, the focus is on the impact of price reduction when FFPs are close to expiration, the supplier order fill-rate for future orders and impact from substitution on demand and inventory.

Due to FFPs short shelf-life, any excess inventory will be prone to the risk of expiration and thus subject to a price reduction. Depending on how excessive the inventory level is, a price reduction can be used as a tool to increase the demand in due time [13]. This decreases the inventory level with the desired speed and timing. Price-elasticity can support the order sizing of FFPs by estimating how much the inventory position will decrease each time products are reduced in the price, and is also suggested by [18].

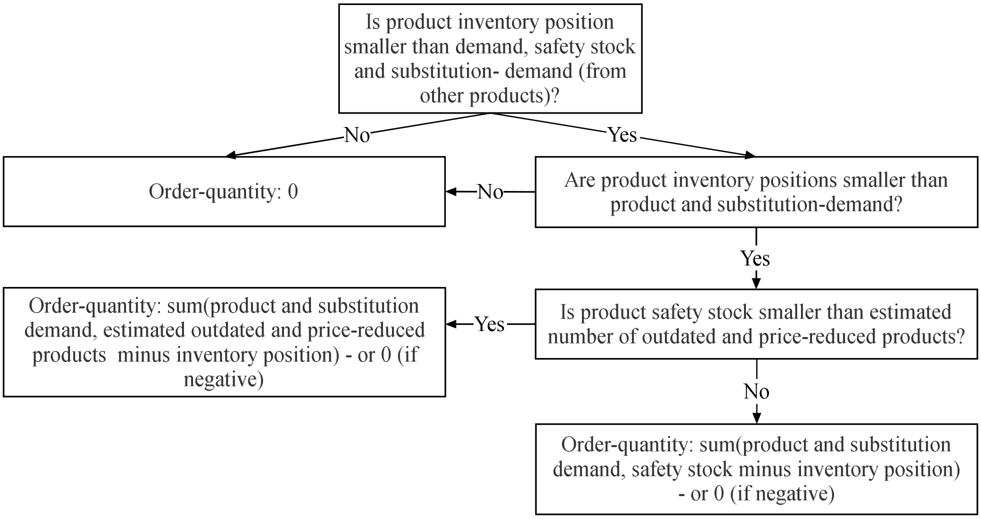
The FFPs are processed down to every day with immediate shipment from the supplier, for fresh meat products see e.g. [17]. The raw materials for FFPs are scarce and can usually not be stored for any longer time, as well as they are often influenced from factors such as, e.g. available only in certain season(s) and nature (storm, rain etc.). Sudden scarcity may, therefore, influence future orders, not yet in transit, within the review period. By including a supplier order fill-rate, this order sizing of FFPs may encounter this and increase order size as needed.

The last two product characteristics concern substitutions and the impact on demand and inventory availability [10, 19]. Focusing on “FFP A”, we consider substitution demand for “FFP A” when “FFP B” has too low inventory, and substitution inventory from “FFP B” when “FFP A” has too low inventory. [10] de-scribes how the well-used exogenous substitution factors may be used for creating a substitution probability matrix. We represent the two by available substitution inventory of other FFPs and substitution demand from other FFPs.

2. A Multi-product EWA with Supplier Fill-Rate, Price Reduction & Substitution

To control inventories in a way which reflects the consumer requirements (availability and freshness) and impact from substitution as well as mitigates the risk of causing quality reduction and food waste, it is necessary to use a multi-product approach. To ensure the size of safety stock relative to outdating products, we build on the EWASS. As with both current EWA policies [5, 7], we use a fixed review period. This fits with the grocery industry and wholesaler/retail stores placing orders at specified time points regardless of demand type (normal or campaign demand). Having a safety stock for perishable items means a chance for reducing the sales price of the product to adjust the inventory position, so waste is avoided. Based on the four FFP characteristics, EWA_{3SL} is suggested. The 3SL in EWA_{3SL} relates to the supplier (S), shelf-life (SL) and substitution (S). It follows the logic as depicted in Figure 1, where one of three different order-sizing decisions applies.

Figure 1: Decision Diagram for EWA3SL



To ensure simplicity in presentation, we first define the available inventory as in equation (3). For product p_1 at time t we consider current inventory level (on hand and in transit), plus all quantities ordered but not yet received/in transit multiplied by the fill-rate (β) for each supplier (l), minus already reserved quantities[18], within the review- and lead-time (i) [15]. Then, the estimated outdated (i.e. expired) quantities and estimated quantities sold at a reduced price (due to close to expiration) up until the immediate prior time period are subtracted. For quantities sold at a reduced price, please notice that there may be products with different expiration dates, i.e. different price-reduced quantities each day as identified by ε.

$$\begin{aligned} I_{p_1,t}^{available} = I_{p_1,t} &+ \sum_{i=t+1}^{R_{p_1}+L_{p_1}} \sum_{l=1}^{S_1 \to S_x} Q_{p_1,i,l}^{ordered} \beta_{p1,i,l} - \sum_{i=t+1}^{R_{p_1}+L_{p_1}} Q_{p_1,i}^{reserved} \\ &- \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \hat{Q}_{p_1,i}^{outdate} - \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{k=1}^{\varepsilon_{p_1}} \hat{Q}_{p_1,i,k}^{reduced} \end{aligned} \tag{3}$$

$I_{p_1,t}$ = starting inventory position, after expired products are subtracted
$Q_{p_1,i,l}^{ordered}$ = number of product p_1 already ordered but arriving later, within review time
$\beta_{p1,i,l}$ = fill-rate on ordered quantities of product p_1 from supplier l $(S_1 \to S_x)$
$Q_{p_1,i}^{reserved}$ = number of product p_1 reserved from inventory due to e.g. campaign or customer

[18] Customer orders placed long time in advance, e.g. pre-orders for campaigns.

$\hat{Q}_{p_1,i}^{outdate}$ = estimated number of product p_1 to expire within review time
$\hat{Q}_{p_1,i,l}^{reduced}$ = estimated number of product p_1 sold a reduced price within review time

In addition to the classical demand plus safety stock as order-up-to point, the EWA3SL considers the substitution effect, when evaluating relative to available inventory. Also, that the substitution for "FFP A" and "FFP B" may not necessarily be one-to-one, i.e. equal interdependence. As example, while a substitute for ground beef 8-12% may be ground beef 4-7%, the substitute for 4-7% may be a completely different product, i.e. thus not necessarily symmetrical demand-effect.

In step 1 (equation 4, below) in the EWA3SL, if the available inventory of product p_1 at time t is less than the sum of expected demand within the review- and lead-time, the safety stock and the expected substitution-demand from other products (not having sufficient inventory) (product *2* to *x*, $p_2 \rightarrow p_x$), then continue to step 2. $E\left[D_{j,i}^{sub}\right]$ is expected substitution demand for all products p_j, when product p_1 has excess inventory and p_j has too low inventory to satisfy demand and thus substitute with product p_1. This is influenced by the substitution probability factor $\mu_{p_1|j}$ for all *j* products [10]. Similarly, when the substituting products p_j have excess inventory, allowing substituting demand from product p_1. In the formula we account for an FFP may have several other substituting FFPs as the case of e.g. multiple brands (brand#1, brand#2 and private label). For expected demand, this may be particularly relevant when a certain product may not be available from supplier for a (longer) period. This is depicted in equation (4).

In step 2 (equation 5), the substituting inventory available from product $p_2 \rightarrow p_x$ is included when evaluating against product $p_1$demand and product $p_2 \rightarrow p_x$ substitution demand. If the total available inventory is less than total expected demand, proceed to step 2a. Here the evaluation of safety stock and outdated/price-reduced products determines the order-size as described by [7]. In the EWA3SL, we additionally add the number of products price-reduced due to close to expiration as well as the substituting demand from other products if safety stock is smaller than the two. This is depicted in equations (5-9).

In step 3, if the available inventory is larger or equal to expected product and substitution demand, no order should be placed. This may be of particular relevance if experiencing too high inventory levels of substituting products that need to be reduced. Depending on the substitutability, different products inventories may be included in the calculation. Thus, EWA3SL includes risk mitigation by evaluating with substitution inventory that could otherwise end up as potential waste if inventory levels are high. This is depicted in equation (10).

1) If:

$$I_{p_1,t}^{available} < \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{p_1,i}\right] + SS_{p_1} + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{j,i}^{sub}\right] \mu_{p_1|j} \tag{4}$$

where:
$D_{j,i}^{sub} = 0 \quad if \quad I_{j,i}^{available} \geq D_{j,i}$ and $D_{j,i}^{sub} > 0 \quad if \quad I_{j,i}^{available} < D_{j,i}$

$$\mu_{p_x|j} = \begin{pmatrix} 0 & \mu_{p_1 2} & \cdots & \mu_{p_1 j} & \cdots \\ \mu_{p_2 1} & 0 & \cdots & \mu_{p_2 j} & \cdots \\ \vdots & \vdots & \ddots & \vdots & \cdots \\ \mu_{p_x 1} & \mu_{p_x 2} & \cdots & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

then,

for all $\boldsymbol{I_{p_x,t}^{available} < E\left[D_{p_x,i}\right]}$,
2) if,

$$I_{p_1,t}^{available} + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} I_{j,i}^{sub.avail.} < \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{p_1}\right] + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{j,i}^{sub}\right] \mu_{p_1|j} \tag{5}$$

then,
2a) if,

$$SS_{p_1} < \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \hat{Q}_{p_1,i}^{outdate} + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{l=1}^{\varepsilon_{p_1}} \hat{Q}_{p_1,i,l}^{reduced} \tag{6}$$

then,

$$Q_{p_1,t} = \max\left(\left(\begin{array}{c} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{p_1}\right] + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \hat{Q}_{p_1,i}^{outdate} + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{l=1}^{\varepsilon_{p_1}} \hat{Q}_{p_1,i,l}^{reduced} \\ + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{j,i}^{sub}\right] \mu_{p_1|j} - I_{p_1,t}^{available} \end{array}\right), 0\right) \tag{7}$$

2b) if,

$$SS_{p_1} \geq \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \hat{Q}_{p_1,i}^{outdate} + \sum_{i=t+1}^{R_{p_1}+L_{p_1}-1} \sum_{l=1}^{\varepsilon_{p_1}} \hat{Q}_{p_1,i,l}^{reduced} \tag{8}$$

then,

$$Q_{p_1,t} = \max\left(\left(\sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{p_1,i}\right] + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{j,i}^{sub}\right]\mu_{p_1|j} + SS_{p_1} - I_{p_1,t}^{available}\right), 0\right) \quad (9)$$

for all $\boldsymbol{I_{p_x,t}^{available} \geq E\left[D_{p_x,i}\right]}$,
3) if,

$$I_{p_1,t}^{available} + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} I_{j,i}^{sub.avail.} \geq \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{p_1}\right] + \sum_{j=1}^{p_2 \to p_x} \sum_{i=t+1}^{R_{p_1}+L_{p_1}} E\left[D_{j,i}^{sub}\right]\mu_{p_1|j} \quad (10)$$

then,

$$Q_{p_1,t} = 0$$

$I_{p_1,t}^{available}$ = inventory position (on hand plus in transit) at time t for product p_1
$I_{j,i}^{sub.avail.}$ = beginning inventory at time i for substituting product *j* $(p_2 \to p_x)$
$\hat{Q}_{p_1,i}^{outdate}$ = estimated number of product p_1 to expire within review time
$\hat{Q}_{p_1,i,l}^{reduced}$ = estimated number of product p_1 sold a reduced price within review time
$E\left[D_{j,i}^{sub}\right]$ = expected substitution demand from product *j* $(p_2 \to p_x)$
$E\left[D_{p_1,i}\right]$ = expected demand from product p_1
SS_{p_1} = safety stock for product p_1
$Q_{p_1,t}$ = order quantity for product p_1
$\mu_{p_1|j}$ = substitution matrix for product *j* $(p_2 \to p_x)$ substituting with product p_1 when $I_{j,i}^{available} < D_{j,i}$
ε_{p_1} = price elasticity of product p_1 for price reduction when p_1 gets close to expiration

3. Conclusion

This study extends the inventory control for stochastic demand and fixed review time to multi-product model, by suggesting a new heuristics considering four product characteristics. The model includes substitution factors across all products as well as includes potential noise in supply-signal through estimated fill-rate during future orders to receive. It is based on previous studies on EWA. By allowing asymmetrical evaluation according to the product characteristics the EWA_{3SL} reflects the real-life situations even more, causing effective decision-making when order-sizing. This means that e.g. the impact from different rounds of price-reduction on the product demand is considered. The EWA_{3SL} is expected to bring even lower waste and improved availability than previous results by supporting the mitigation of risks across products. For practical implications, determining the substitution factor may be challenging and rather subjective given the limited literature on the subject matter and the influence from geographical area, culture etc. [10, 19]. A solution may be to then apply a binary system: 0 if not substitutable and 1 if substitutable. Further, the model is yet to be tested, and further research govern checking how robust the heuristic is, the impact on inventory levels, fill-rate and waste.

References

1. Hübner, A.H., Kuhn, H., Sternbeck, M.G.: Demand and Supply Chain Planning in Grocery Retail: an Operations Planning Framework. Int. J. Retail Distrib. Manag. 41, 512–530 (2013). https://doi.org/10.1108/IJRDM-05-2013-0104.
2. BlueYonder: Customer Experience in Grocery Retail: the Fresh Opportunity Customers in Fresh - A Global Survey of 4,000 Consumers Shine Light on Customer Experience in Fresh and Product Availability. (2017).
3. Mena, C., Terry, L.A., Williams, A., Ellram, L.M.: Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector. Int. J. Prod. Econ. 152, 144–158 (2014). https://doi.org/10.1016/j.ijpe.2014.03.012.
4. Broekmeulen, R.A.C.M., van Donselaar, K.H.: Quantifying the Potential to Improve on Food Waste, Freshness and Sales for Perishables in Supermarkets. Int. J. Prod. Econ. 1–9 (2017). https://doi.org/10.1016/j.ijpe.2017.10.003.
5. Broekmeulen, R.A.C.M., van Donselaar, K.H.: A Heuristic to Manage Perishable Inventory with Batch Ordering, Positive Lead-Times, and Time-Varying Demand. Comput. Oper. Res. 36, 3013–3018 (2009). https://doi.org/10.1016/j.cor.2009.01.017.
6. RELEX: Planning for Every Future in Grocery Retail, Survey-Based Research Study. (2020).
7. Kiil, K., Hvolby, H.H., Fraser, K., Dreyer, H., Strandhagen, J.O.: Automatic Replenishment of Perishables in Grocery Retailing: The Value of Utilizing Remaining Shelf Life Information. Br. Food J. 120, 2033–2046 (2018). https://doi.org/10.1108/BFJ-10-2017-0547.
8. Duan, Q., Liao, T.W.: A New Age-Based Replenishment Policy for Supply Chain Inventory Optimization of Highly Perishable Products. Int. J. Prod. Econ. 145, 658–671 (2013). https://doi.org/10.1016/j.ijpe.2013.05.020.
9. Lowalekar, H., Ravichandran, N.: A Combined Age-and-Stock Based Policy for Ordering Blood Units in Hospital Blood Banks. Int. Trans. Oper. Res. 24, 1561–1586 (2017). https://doi.org/10.1111/itor.12189.
10. Hübner, A.H.: Retail Category Management Decision Support Systems. In: Lecture Notes in Economics and Mathematical Systems. Springer (2011).
11. Steven Nahmias: Perishable Inventory Theory : A Review. Oper. Res. 30, 680–708 (1982).
12. Raafat, F.: Survey of Literature on Continuously Deteriorating Inventory Models. J. Oper. Res. Soc. 42, 27–37 (1991). https://doi.org/10.1057/jors.1991.4.
13. Goyal, S.K., Giri, B.C.: Recent Trends in Modeling of Deteriorating Inventory. Eur. J. Oper. Res. 134, 1–16 (2001). https://doi.org/10.1016/S0377-2217(00)00248-4.

14. Bakker, M., Riezebos, J., Teunter, R.H.: Review of Inventory Systems with Deterioration Since 2001. Eur. J. Oper. Res. 221, 275–284 (2012). https://doi.org/10.1016/j.ejor.2012.03.004.
15. Silver, E.A., Pyke, D.F., Peterson, R.: Inventory Management and Production Planning and Scheduling. John Wiley & Sons, Inc., Hoboken (1998).
16. Nahmias, S., Pierskalla, W.P.: Optimal Ordering Policies For a Product That Perishes in Two Periods Subject to Stochastic Demand. Nav. Res. Logist. Q. 20, 207–229 (1973). https://doi.org/10.1002/nav.3800200202.
17. Christensen, F.M.M., Jonsson, P., Dukovska-Popovska, I., Steger-Jensen, K.: Differentiated Demand Information Sharing in Perishable Product Supply Chains: A Supplier Planning Environment Contingency. Prod. Plan. Control (Under Rev. (2020).
18. van Donselaar, K., van Woensel, T., Broekmeulen, R., Fransoo, J.: Inventory control of perishables in supermarkets. Int. J. Prod. Econ. 104, 462–472 (2006). https://doi.org/10.1016/j.ijpe.2004.10.019.
19. Gruen, T.W., Corsten, D.S., Bharadwaj, S.: Retail Out-of-Stocks: A Worldwide Examination of Extent, Causes and Consumer Responses. Grocery Manufacturers of America, Washington (2002).

PAPER #9

Real-Time Point-of-Sales Information Sharing in Fresh Food Supply Chain

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The PhD student defined the problem and proposed the structure and core scientific idea to solve it. The PhD student derived key-methodology, conducted case-study research and interviews, collected and analysed data, wrote the entire draft version of the paper, and re-vised it according to co-authors comments.

Real-Time Point-of-Sales Information Sharing in Fresh Food Supply Chain

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Abstract. This study empirically tests the effect of sharing real-time POS-based demand information be-tween the wholesaler and fresh food product processor during order decision-making. The effects are assessed across different demand types and product processing methods. The research design is a multiple case study covering five fresh food processors, one wholesaler and a retail chain with 329 retail stores. The analysis investigates the effect on fill-rate, product freshness, inventory lev-el and waste-levels, by comparing against order-based information sharing and a mix of both real-time POS- and order-based information sharing. Findings show that real-time POS-based information sharing generally outperforms order-based information sharing and that mixed information sharing at product level leads to the most significant improvement in performance. Further, the performance differs across demand type and processing method and an increase in performance is generally seen by a marginal reduction in fill-rate, while significant reduction in waste-levels and increase in freshness.

Keywords: point-of-sales, real-time, information sharing, perishables, forecasting, inventory control

1. Introduction

Fresh food product (FFP) supply chains struggle to meet the consumer requirements for availability and freshness (Aastrup and Kotzab, 2009; Kuhn and Sternbeck, 2013). Also, inappropriate replenishment planning and control

(RP&C) cause high waste level (Eriksson et al., 2014; Mena et al., 2011, 2014). As opposed to e.g. historical store orders, point-of-sale (POS) data is often considered the most accurate demand signal for RP&C, whether demand/order forecasting (e.g. Williams and Waller, 2010, 2011) or inventory control (e.g. Fransoo and Wouters, 2000). However, utilising POS data is challenging and the effect of POS-based demand information depends on e.g. how the demand is characterised (e.g. Steckel et al., 2004).

When no vendor-managed set-up is used, the wholesaler shares demand information with the FFP processor when sending daily orders, based on POS/order information available up until a certain time-point prior to the order decision-making (e.g. van Donselaar et al. (2010)). The de-mand information is typically shared at the same time point (as an order) for all FFPs processed by the given FFP processor. Since this is often hours/day(s) in advance of production scheduling, the information thus reflect historical rather than fresh real-time demand at the time of pro-cessing. Particularly for short shelf-life FFPs, orders which are based on older information and shared longer time in advance may lead to reduced availability and freshness as well as increased waste levels due to the increased forecasting inaccuracy and thus inappropriate order-sizing. In fact, postponing the demand information sharing may be beneficial during campaigns, as it allows to capture the latest demand fluctuations and “base the order on the actual sales” (Kaipia et al., 2013, p. 272). Further, the retail stores continuously sell FFPs after the wholesaler shares the order – even up until/during the processing (scheduling). This may allow the wholesaler to create and share real-time POS-based demand information at any time during the day, instead of the com-monly applied batch (e.g. daily) sharing of historical order-based demand information. Thereby operating even closer to the actual demand and minimise losses i.e. lost sales and waste.

Real-time information sharing has already been around for years in internal IT systems (e.g. ERP and production systems). Today, real-time sharing is possible across external IT systems due to the technological advancements during recent years. Yet, retrieving, handling and computing the (raw) POS data from hundreds of retail stores and up to thousands of products in real-time, and subsequently forwarding the POS-based information to multiple (FFP) processors, causes enormous pressure on the IT-systems. The wholesaler may not even have the technological advancement required, and not all FFPs may benefit to the same extent. Thus, merely sharing information in real-time for all FFPs may cause an increased risk of loss and excessive or redundant use of IT-systems.

Further, it is widely recognized that e.g. product type layout, sequence-dependent setup and variable processing times (in this study, collectively termed processing method) impact the pro-duction planning and scheduling (Entrup, 2005; Romsdal, 2014). Since FFPs have short shelf-life and are processed daily, then considering the processing method when timing the information sharing during RP&C may also minimise losses. However, it is not clear if – and to what extent – differentiating the real-time POS-based/historical order-based information sharing at a product level according to a processing method improves the performance.

No identified study empirically explores the effect of sharing real-time POS-based information for FFPs at different time-points during RP&C i.e. demand forecasting and inventory control combined into one process. Also, no study focuses on when it is valuable to share real-time POS-based information over order-based, considering the demand type and processing method at a product-level. To investigate these aspects, this study develops research hypotheses for construct-ing and testing multiple information sharing scenarios across different processing methods and demand types. This is the first study considering both demand forecasting and inventory control combined based on real-life data from fresh meat products in retail supply chain computing real-time information sharing. The following presents the theoretical background and the research hypotheses to be tested. Then the methodology presents the empirical cases as well as the computational model used in this study. The Results section summarizes the effect on product availability, freshness and waste-levels according to individual processing method and demand type. This pa-per contributes to the existing literature by providing empirical and contextual insights on real-time POS-based information sharing in the FFP supply chain, given different demand types and processing methods. It gives information about the effect of sharing real-time POS-based vs his-torical order-based information.

2. Theoretical Background & Research Hypotheses

Replenishment planning and control (RP&C) relates to the "operational planning and control of inventory replenishment in supply chains" with vast focus on information sharing (Jonsson and Holmström, 2016, p. 64). Two main parts of FFP RP&C from a wholesaler point of view is predicting the upcoming demand from retail stores (forecasting) and determining the quantity to or-der from the FFP processor (inventory control). For forecasting, two general planning purposes are dominant: demand planning (i.e. forecasting consumer demand) and order-fulfilment planning (i.e. forecasting incoming orders) (Narayanan et al., 2019). The objective for demand planning is matching overall supply with consumer demand, while for order-fulfilment ensuring enough inventory to fill incoming orders. While separating the two is straightforward when handling non-perishable items, it is less so for FFP supply chains. In a non-perishable context, inventories balance demand and order-fulfilment planning, by encompassing the fluctuations in order-size and deviations from POS data (discussed shortly). For short shelf-life FFPs, inventory building is in-appropriate per se. Rather the wholesaler orders should reflect the retail store orders and POS de-mand on a 1:1 basis, to ensure a continuous flow of FFPs with daily deliveries. For inventory con-trol, multiple approaches exist, mainly differing in fixed/variable timing, continuous/periodic re-view period and fixed/variable quantity (Silver et al., 1998).

2.1. Sharing and utilising POS data along with its challenges

Sharing and utilising the POS data reduces product shortages and demand amplification (i.e. bull-whip effect) (Croson and Donohue, 2003; Småros et al., 2003) as well as demand/supply planning nervousness (Kaipia et al., 2006). The POS data is typically shared either directly from retail store to wholesaler/FFP processor or through wholesaler to FFP processor, either daily or weekly (e.g. Alftan et al., 2015; Pramatari and Miliotis, 2008; Ståhl Elvander et al., 2007). Depending on the level of collaboration, the POS data is used in decentralised decision-making (e.g. vendor man-aged inventory (Ståhl Elvander et al., 2007)), centralised decision-making (e.g. collaborative buy-er-managed forecasting (Alftan et al., 2015)) or collaborative decision making (e.g. collaborative planning forecasting and replenishment (Aviv, 2007)).

A premise for effective POS data sharing is utilisation, i.e. that the POS data is "incorporated and actually used in the information receiver's planning processes" (Jonsson and Myrelid, 2016, p. 1769). However, FFP processors struggle to use the raw and/or store level POS data to forecast wholesaler orders accurately, due to the increased volatility when comparing against aggregated POS data from all retail stores (Williams and Waller, 2010). Also, effective utilisation of the raw POS data is challenging for FFP processors when forecasting demand and improving processing planning (i.e. master production scheduling (MPS)). This, due to the high level of detail and lack-ing reflection of downstream behaviour and operations (Narayanan et al., 2019; Raman et al., 2001; Williams et al., 2014). Merely receiving raw POS data without any additional information may lead to wrongful conclusions about future demand (Kembro and Selviaridis, 2015). The POS data does not reflect needs to: buffer against uncertainties or use stored volumes, adjust order quantities (to account for product cannibalisation/substitution) or actual inventory levels (may be lower than seemingly due to, e.g. shrinkage). Thus, to ensure knowledge about product availability and to determine the order size effectively, the POS data should be complemented with infor-mation about, e.g. planned store/wholesaler orders, historical store/wholesaler orders, store campaigns and store/wholesaler inventory records (Alftan et al., 2015; Williams et al., 2014; Williams and Waller, 2011).

2.2. Historical order and POS data in demand forecasting and inventory control at wholesaler

The impact of POS data on RP&C (i.e. demand forecasting or inventory control) in a grocery re-tailing context is studied to some extent. Table 1 summarises and provides a selected overview of recent empirical studies focusing on grocery retailing and food products, from a wholesaler and retail store point of view. To narrow focus and increase relevancy, a semi-structured literature review was carried, searching for (real-time) point of sales, order (decision-making), inventory control, (demand) forecasting, grocery retailing and fresh food products. Spelled in different ways, a search was carried out in four major databases (ProQuest, Emerald Insight, Elsevier and ABI/INFORM). Snowballing was also used within recent literature. Each study is depicted as to its RP&C field and supply chain focus with information about the products, demand, aggregation level, decision horizon and observed improvements. Also, brief summaries of the studies are provided. From the selected studies, six focus on weekly level demand forecasting (Hartzel and Wood, 2017; Jin et al., 2015; Williams and Waller, 2010, 2011), while four on daily in terms of both demand forecasting (Huber et al., 2017; Narayanan et al., 2019) and inventory control (Ehrenthal et al., 2014; Williams et al., 2014).

In general, the studies reflect total daily/weekly demand per product and mainly with a weekly decision horizon. Regarding supply chain focus, most studies include distribution centre and/or retail store(s), while only three studies include supplier stage. The performance measures com-monly used reflect forecasting accuracy and costs, rather than consumer specific measures such as waste, fill-rate and freshness. Current studies focus on when POS-data/-based order information is more valuable than order-based for different demand types, e.g. seasonal, regular or campaign (see e.g. Jin et al. (2015), Williams and Waller (2014; 2010)). However, they use different products mainly with longer shelf life, often at weekly level sharing. No study compares two demand types and in real-time across a same sample of products.

For POS-/order-based demand forecasting, Hartzel and Wood (2017) find that the POS-based forecasts generally outperform order-based forecasts, and have the most positive effect when the frequency of product orderings is low, the number of orderings during a week have little variance, and the ordered quantities are neither relatively high nor relatively low. Williams and Waller (2010) find that POS data generally leads to more accurate forecasts, but when order-data is best it leads to more significant improvements. In contrast, order-data has a positive effect when there is influence from high bullwhip effect and high demand “created by supplier programs designed to increase an SKU’s volume through promotional activity” (2010, p. 240). Narayanan et al. (2019) differ between planning purpose and find that sharing POS data between store and supplier has a positive effect on the forecasting accuracy for matching overall supply with downstream demand (i.e. demand planning). However, a negative effect when ensuring sufficient inventory levels to meet incoming orders (i.e. order-fulfilment planning). Williams and Waller (2011) find that while POS data increase forecasting accuracy and improve performance for inventory/transportation planning, it is questionable for production/capacity planning. Further, they find that supply chains with few distribution centres may benefit more from POS data sharing, than supply chains with several distribution centres, due to risk pooling. Huber et al. (2017) find that clustering POS-demand according to intra-sales patterns, leaves substitutable items in the same clusters and that accordingly aggregation of POS-demand both increase availability and limit losses.

For inventory control, Ehrenthal et al. (2014) find that sharing POS data has a positive effect on the inventory decision-making when the demand is stable and characterised by seasonality across weekdays. “Across-days variations have a greater impact than intra-day variations. Taking intra-day variations into account without acknowledging across-days variations can lead to an increase in costs, i.e., more information is not always better” (2014, p. 528). Williams et al. (2014) find that by including both POS data and orders “suppliers subsequently account for how changes in the retailer’s echelon inventory position influence the retailer’s future orders in addition to de-mand and order patterns” (2014, p. 598).

Table 1: Empirical POS data literature on demand forecasting and inventory control in grocery retailing context

Author	Brief summary	RP&C field	Supply chain focus	Products	Information shared	Data dimen-sions	# of products	Aggre-gation	Decision-horizon	Improve-ment measure
Ehrenthal et al. (2014)	Uses POS data to investigate the value of considering demand seasonality in inventory problem where demand has a known season length, the lead time is shorter than the review period and orders are placed as multiples of a fixed batch size.	IC	RS	Energy drink, milk, lettuce, sausage, eggs, caffeinated soda, croissants, cigarettes, potato chips, orange juice	Raw POS data	one-year POS data from one RS	1000	Product	One day review (overlapping two days)	Supply chain costs: ordering, handling, purchasing, holding and penalty for unmet demand
Hartzel and Wood (2017)	Examines and compared POS-based and order-based demand forecasting, by focusing on the factors related to the improvement of POS-based demand forecasting.	DF	MA ↔ (DC ↔) R	Mixed food products	Raw POS data, customer orders	60,651 orders for 10 months from 25 DCs	494	Summed orders	Short-term, weekly	Order quantity, item order frequency

Author	Brief summary	RP&C field	Supply chain focus	Products	Information shared	Data dimen-sions	# of products	Aggre-gation	Decision-horizon	Improve-ment measure
Huber et al. (2017)	“Propose a DSS that supports day-to-operations by providing hierarchical forecasts at different organizational levels based on most recent point-of-sales data” (p. 140) using ARIMA(X) and comparing forecasting accuracy.	DF	DC ↔ RS	Bakery (buns and breads)	Raw POS data	18 months POS data from 6 RS	16	Product	Short term, daily	MSE
Jin et al. (2015)	Examines demand and order forecast at aggregated (monthly) and disaggregated (weekly) level in terms of information loss and variance reduction using Holt’s exponential smoothing.	DF	SU ↔ DC ↔ RS	Dry grocery products and fresh, refrigerated products that have short shelf-lives	Week-level POS data, DC orders	104 observations for 104 weeks from six DCs and six RS	14	Products per week	Weekly and monthly	MAD, one-way analysis of variance
Narayanan et al. (2019)	“Explore what actually happens to forecast accuracy for demand and order-fulfillment planning	DF	SU ↔ DC ↔ RS	Cereal adult, cereal children, detergent,	POS data, orders	two years of daily POS data and three months of	21	Product	Short term (R, mQ)	wMAPE

Author	Brief summary	RP&C field	Supply chain focus	Products	Information shared	Data dimen-sions	# of products	Aggre-gation	Decision-horizon	Improve-ment measure
	when the forecast demand signal is based on POS, retailer orders, or distribution center (DC) orders” (p.468)			cosmetics, pizza		RS orders for each SKU and inventory stocking point from two DC and 271 RS				
Williams and Waller (2010)	Compares “the effectiveness of POS and order data to forecast DC orders”, by investigating “the frequency with which POS data provides increased order forecast accuracy” and “the magnitude of improvement that POS data provides (p. 232)	DF	DC ↔ RS	Cereal, canned soup and yogurt products	POS data, orders	Two years of weekly POS and order data	10	Product	Short-term, weekly	MAD, MSE
Williams and Waller (2011)	“Investigate two demand forecasting issues: (1) the accuracy of top-down versus bottom-up demand forecasts; and (2)	DF	DC	Ready-to-eat cereal products	POS data	Two years of weekly POS and order data from 18 DC and 180 RS	10	Product per RS	Short term, weekly	MAPE, MSE

Author	Brief summary	RP&C field	Supply chain focus	Products	Information shared	Data dimen-sions	# of products	Aggre-gation	Decision-horizon	Improve-ment measure
	whether shared POS data improve demand forecast accuracy" (p. 17)									
Williams et al. (2014)	"Based on the inventory balance effect, this research prescribes a forecasting approach which simultaneously uses both sources of information (retailer order history and POS data) to predict retailer orders to suppliers" (p. 593)	IC	DC	Six dry grocery products	Week-level DC orders, POS data	110* weeks DC orders and POS data from one MA and nine retail DCs	6	Product	Short term,	MAPE, HLM

* *104 weeks treated as in-sample, 6 weeks as out-of-sample*

Note: RP&C field: IC = Inventory control, DF = demand forecasting

Supply chain focus: SU = supplier, MA = manufacturer, DI = distributor, DC = distribution centre, WH = wholesaler, R = retailer, RS = retail stores

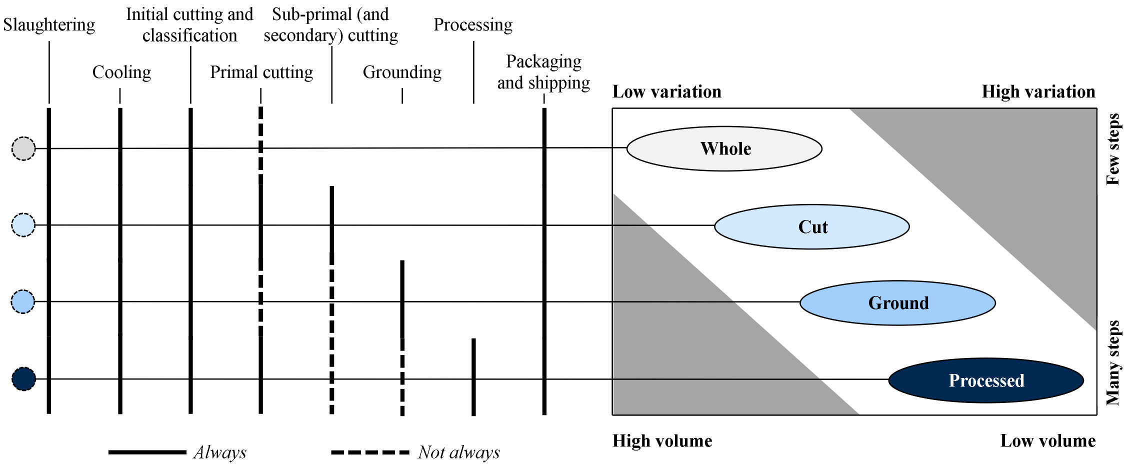
Improvement measure: (w)MAPE = (weighted) mean absolute percentage error, (R)MSE = (root) mean squared error, MAD = mean absolute deviation, HLM = hierarchical linear model

2.3. Fresh food products and their processing

Processing raw-materials into FFPs is specialised and product-dependent (Entrup, 2005; Romsdal, 2014). The FFP processor's master production schedule (MPS) details when and how much to process at a given time. Thereby also the timing for information sharing. Planning environment characteristics impact the MPS, and to what extent an already scheduled/ongoing MPS might be altered. The literature highlights multiple planning environment characteristics related to the intrinsic product and the processing (Dreyer et al., 2018; Ivert et al., 2015; Jonsson and Mattsson, 2003; Romsdal et al., 2014; Spenhoff et al., 2014; Wänström and Jonsson, 2006). Depending on how an FFP is processed, few or several characteristics put forth different constraints and requirements onto the MPS, impacting the extent to which real-time sharing has greater effect than historical or not. As an example, for an FFP with few processing steps and short processing lead-time, it is easier to adjust the processing quantity than for an FFP with multiple processing steps and long processing lead-time (e.g. maturity/ageing).

Figure 5 illustrates the overall processing methods of four types of fresh meat products. Due to the focus on information sharing and to simplify, processing method is used as an umbrella-classification for the FFP types to encompass the planning environment characteristics collectively. Processing method conveys the grouping of products following how the products differ on an aggregated level from a FFP wholesaler point of view. The FFPs may be as whole parts requiring mere slaughtering and cleansing (e.g. whole chicken), cut into slices requiring primal cutting (e.g. steaks), ground according to specific requirements requiring primal and secondary cutting (e.g. ground meat), or processed with additional materials requiring primal and secondary cutting as well as batch-based processing (e.g. marinated meat). The different processing steps are shown in relation to the product-process matrix (Hayes and Wheelwright, 1979). Entrup (2005) differentiates the customer order de-coupling point (CODP) depending on if the product is produced in large volumes (CODP can be earlier, meaning that some can be produced to stock), vs special products (so CODP can be later, for example in packaging). As an ex-ample, while whole FFPs have low variation (thus early customer order de-coupling point (CODP)) with few processing steps, processed FFPs have high variation (and late CODP) with many processing steps.

Figure 5: Product-process matrix, adapted from Hayes and Wheelwright (1979)



2.4. Development of research hypotheses

From the studies, it seems that there is a general ackowledgement of POS data having a positive effect on both demand forecasting and inventory control. Furthermore, postponing the demand information sharing until later is "especially important during weekends, campaigns, or other periods that cause seasonal variation in demand" since reflecting actual sales (Kaipia et al., 2013, p. 271), entailing a focus on real-time sharing. However, the focus has been on analysing the value from using/sharing (historical) POS data, given a limited number of demand characteristics such as demand type (campaign/regular/ seasonal), demand variation, and inventory level.

Prescriptive and contextualised research founded in empirical evidence is largely missing, leaving practitioners with a lack of research-based understanding on when real-time POS-based information sharing improves freshness and availability of FFPs while reducing waste-levels. No clear recommendations, propositions or framework were found for when to share real-time POS-based information vs order-based demand information with differentiation in timing at the product level. The literature focus is generally on the sharing of POS data rather than sharing the centralised POS-based demand information, as suggested in CBMF (Alftan et al., 2015). However, the CBMF entails a VMI replenishment by the FFP, long-term forecasting (months) and lacks empirical validation of the effect from utilising POS data in centralised forecasting. Entailing RP&C at the wholesaler, leaves room for investigating, what is the effect of real-time POS-based information sharing. And subsequently, what is the effect for campaign vs normal demand, where nor-mal demand includes products not sold a campaign price e.g. regular, seasonal and holiday sales. This is particularly interesting since campaigns heavily influence the grocery industry, and so the product availability (Aastrup and Kotzab, 2010). Since campaign demand has more variation than normal, the performance of RP&C is expected to be lower, since greater forecasting inaccuracy. However, since postponing the timing for demand information sharing it is hypothesized that the performance will improve (Kaipia et al., 2013).

Therefore, we posit the following research hypotheses, where H1a and 1b specifically address normal or campaign demand. It is expected that they will clarify whether real-time POS-based information sharing has a positive or a negative effect on the performance, i.e. product availability, freshness and waste levels.

H1a) During *normal* demand, real-time POS-based information sharing has a *positive* effect on performance.
H1b) During *campaign* demand, real-time POS-based information sharing has a *positive* effect on performance.

Studies investigating the value of POS data/POS-based demand information sharing consider products as either share for all or none. No (empirical) studies focus on what is the effect of wholesaler utilising *real-time* POS-based information in the FFP supply chain at a product-level. Since FFPs have both different demands and are affected differently by a campaign, we assume that by differentiating the way of sharing information at the product level, the aggregated effect will improve the performance for normal demand. For campaign demand, we expect that the differentiation will allow further improvement compared to H1b. Accordingly, we posit the following research hypotheses as an extension to H1a and H1b:

H2a) During *normal* demand, product-differentiated information sharing *improves* the effect on performance compared to non-differentiated order- and real-time POS-based sharing.
H2b) During *campaign* demand, product-differentiated information sharing *improves* the effect on performance compared to non-differentiated order-/real-time POS-based sharing.

Apart from the demand type, the processing method is a grouping of products used in grocery industry. The four types of meat FFPs also reflect different processing characteristics i.e. different impact on FFP processor's production planning i.e. MRP and MPS. Despite the recognition of the processing characteristics' (individual) implications for planning, no empirically grounded study provides evidence about the extent to which the grouped way of sharing information impacts the performance given the differences in terms of variations and processing steps (Figure 5). Accordingly, we posit an extension to each of the above two sets of hypotheses, investigating how the processing method of FFPs moderates the performance. Thereby advancing the “individually or all”-approach discussed above as to what extent processing method is beneficial.

H3a) During *normal* demand, processing-differentiated real-time POS-based information sharing *improves* the effect on performance compared to non-differentiated order- and real-time POS-based .

H3b) During *campaign* demand, processing-differentiated real-time POS-based information sharing *improves* the effect on performance compared to non-differentiated order- and real-time POS-based .

H4a) During *normal* demand, processing- and product differentiated information sharing *improves* the effect on performance compared to non-differentiated order- and real-time POS-based .

H4b) During *campaign* demand, processing- and product differentiated information sharing *improves* the effect on performance compared to non-differentiated order- and real-time POS-based .

Table 1 summarises the hypotheses and indicates the expected relative effect (↓ impaired effect, → no effect, ↗ positive effect and ↑ most positive effect), split across demand type and if processing method is considered or not.

Table 1: Summary of research hypotheses

	Normal demand	**Campaign demand**
Not considering processing method	↗ H1a *(real-time)* ↑ H2a *(differentiated)*	↗ H1b *(real-time)* ↑ H2b *(differentiated)*
Considering processing method	↗ H3a *(real-time)* ↑ H4a *(differentiated)*	↗ H3b *(real-time)* ↑ H4b *(differentiated)*

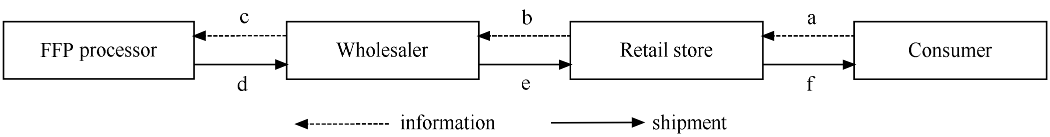
3. Method & Computation Model

We select an exploratory multiple case-study (Flynn et al., 1990) to compare order-based and real-time POS-based information sharing as well as a mix of the two, and investigate the effect on performance. Case-study approach allows insight and evidence for theoretical elaborations (Yin, 2014) along with a deep understanding of practises and processes in a real-world context (Eisenhardt, 1989; Meredith, 1998). Using multiple FFPs for an entire retail chain reduces the risks of misunderstanding and false generalisation from single products/retail stores, and increas-es the external validity (Barratt et al., 2011; Eisenhardt, 1989). Actual empirical constraints and demand were used for demand forecasting and order decision-making. Thereby overcoming short-comings of e.g. distribution fitting from simulation-based approach and generalization from analytical approaches.

3.1. Information sharing context: supply chain focus

A Danish supply chain was selected comprising of five meat processors (beef, pork, chicken and seafood), one wholesaler and a retail chain with 329 stores. This, since meat products deteriorate differently and fast without options for storing (Evans, 2016) and the supply chain is characterised by daily ordering and delivery supporting the premise for the study (i.e. no inventory building). An ongoing research collaboration with the wholesaler and retail chain allowed access to pro-cessing information at FFP processors and detailed POS data from retail stores. The processing information concerned processing capacity limits in form of max additional capacity available per product per day during the period, indicated as a percentage of a given day's order-size. The wholesaler supplies 329 retail stores through one warehouse. The retail stores are driven on franchise-basis and spread across the entire Denmark. The supply chain is characterised by three replenishment cycles as illustrated in Figure 1 and described in the following.

Figure 1: Diagram of supply chain activities and mechanisms



a) Consumers purchase FFPs, thus point-of-sales data is created.

b) Retail store(s) places a new order at the wholesaler every day no later than 11:00 for picking at the wholesaler the same day. The order size is based on the stores' inventory management policies and expected sales (experience-based) until the next delivery to ensure availability.

c) The wholesaler places an order at the processor no later than 16:00 with delivery the following day before 13:00. The order size is based on forecasts of retail stores' future demand and excessive products in the warehouse (cf. inaccurate order sizing the previous day).

d) After receiving the wholesaler's order, the processor schedules the production. The production quantity reflects the actual order (alike make-to-order environment). Production starts from around 22:00 (FFP processor dependent). When the order is processed and packed, the products are shipped to the wholesaler.

e) The wholesaler picks, packs and ships orders to retail stores daily according to actual orders received. An individual store may receive the order later the same day or during the following night.

f) Retail store sells fresh food products to consumers every day during opening hours, from 08:00 to 21:00 (22:00 for some stores).

The focus is on the demand information sharing in the supply chain i.e. the POS data (a), nor-mal/campaign retail store orders (b), inventory levels at wholesaler and wholesaler order (c), delivered wholesaler order and processing information (d) and fill-rate to retail stores (e). Subsequently, measure the effect on product availability, freshness and waste-levels (flows d and e).

3.2. Information sharing context: demand data and product types

Fifty FFPs are selected based on having high demand and be one of four main-animal types. Table 2 depicts how the FFPs are grouped across processing methods, with examples. For quantitative data, we used ten months aggregated (chain-level) and two months of detailed data (store-level). The ten months aggregated demand data from 304 days concerned ordered and delivered wholesaler orders and retail store orders (split into normal and campaign demand) as well as daily-aggregated POS data. The two months demand data concerned additional wholesaler inventory levels, processing information and detailed POS data reflecting the quantity sold per product per day per second. The POS data is created from 07:00 in the morning until 22:00, depending on the store. We include until 23:00 to encompass delays in data transfer.

Table 2: Product types

Processing method	**Beef**	**Pork**	**Chicken**	**Fish**	**Total**	**Comment – FFPs made from…**
Whole	*0*	*0*	*1*	*4*	*5*	*… meat with minimal cutting and no additional ingredients, e.g. whole chicken or whole salmon*
Cut	*13*	*5*	*2*	*2*	*22*	*… meat cuttings sliced into smaller pieces, e.g. pork chops, ribeye steaks, chicken breast filet and salmon filet*
Ground	*3*	*2*	*1*	*0*	*6*	*… single meat type that is ground, e.g. ground beef (3-7%, 8-12%, 15-18%) or ground pork (6-10%, 8-10%)*
Processed	*7*	*3*	*2*	*5*	*17*	*… two/more types of meat or one type of meat added spices that have been ground, e.g. ground fish, meat or sausages* *… meat cuts marinated in batches, e.g. garlic marinated shrimps* *… ground meat or meat cuttings mixed with non-meat ingredients, e.g. patties wrapped in bacon or chicken in curry*
Total	23	10	6	11	50	

Table 3 shows which data was collected and where, around 8.3 million data points. The processing information was collected by the procurement department at the wholesaler and reflected the allowed quantity changes during the processing per FFP per day. The wholesaler order reflects the forecasted demand plus an added extra quantity by the purchaser to account for forecasting uncertainty. The normal/campaign store orders reflect the individual store as actual sales plus an added extra quantity to account for the uncertainty from expected sales until next delivery (i.e. the day after). The detailed POS data was retrieved manually from each of the 329 retail stores' cashier systems since not available centrally at retail chain/wholesaler. The inventory, master and conversion data were collected through ERP-, WMS- and other IT-systems from the wholesaler. Conversion data was used for calculating unit size between store and wholesaler (pieces vs package). Since the retail chain is franchise-based, each store controls sales prices, markdowns etc. Thus, price information for each POS-transaction was also collected to be able to sort out and take into consideration "unusual demand" from products sold at a reduced price due to, e.g. date-expiration or local/national campaign/promotion. The demand is characterised by a rapid increase in a long campaign (Sunday to Saturday) and short campaign (Thursday to Saturday) periods as well as seasonal demand for some products.

Table 3: Quantitative data collected per period and supply chain stage

Period	FFP processor	Wholesaler	Retail store
Sep'19-Oct'19	- processing information (2,655)	- wholesaler order, ordered (2,655) - wholesaler order, delivered (2,655) - *normal* store order, agg. ordered (2,366) - *normal* store order, agg. delivered (2,366) - *campaign* store order, agg. ordered (802) - *campaign* store order, agg. delivered (802) - inventory level (3,721)	- POS data, detailed (5,610,009)
Nov'18-Aug'19		- *normal* store order, agg. ordered (10,035) - *normal* store order, agg. delivered (10,035) - *campaign* store order, agg. ordered (3,835) - *campaign* store order, agg. delivered (3,835) - master data - conversion data	- POS data, aggregated (13,598)

3.3. Running the real-time POS data sharing scenarios

All scenarios were run with the two different demand types. First, an as-is performance based on extracted historical data is analysed directly to control for inconsistencies in the data that had to be taken care of in the further scenario development (e.g. missing data in some periods). Since historical performance data reflect the ongoing (human) evaluation, judgment and adjustment happening to forecasting, order-sizing and inventory level on an ad-hoc basis, it is excluded in the further evaluation.

In scenario S2 historical store orders are input for demand forecasting, without any real-time POS data sharing. Inventory levels (resulting from forecasting inaccuracy) and wholesaler orders are derived from the demand forecast. The mean historic fill-rate per product per FFP processors is used for delivered wholesaler order.

In scenario S3, we compute as in S2, but instead of using historical orders to forecast demand, we now use real-time POS data. To simplify and reduce computing, we use real-time POS data sharing from retail stores on hourly interval during opening hours, i.e. at 07:00, 08:00 … and 23:00. This means that for each of the 50 FFPs, we run the model 16 times (hence S3a/.../S3p), each with updated POS data according to the time for sharing, e.g. if sharing at 16:00, we use the cumulative POS sales data at 16:00. For wholesaler orders shared differently than in S2, we use the mean delivery performance for all products the entire period (assuming delivery performance is normally distributed). For order-quantities larger than those in S2, we use the processing information from the FFP processor to increase the processing order accordingly (per day per product). For quantities smaller than those in S2, the min-limit is zero.

In S4, we compare S2 and S3a/.../S3p and choose the scenario with best forecasting accuracy for each product. This means that S4 represents some FFPs with order-based information sharing and some with real-time POS-based information sharing at different time-points during the day.

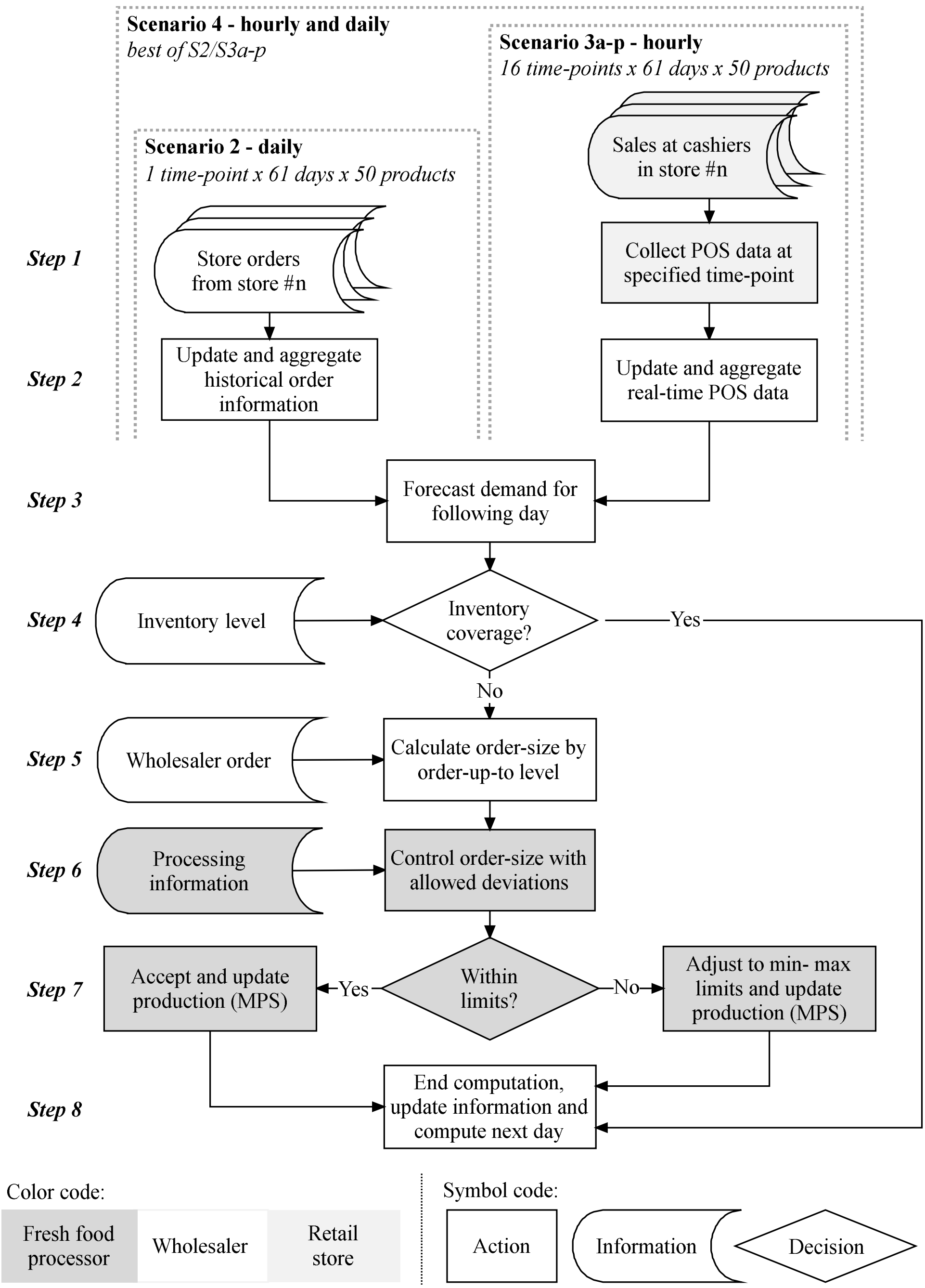
We compute 850 different scenarios (50 FFPs * (1*S2 + 16*S3a-p)). Scenario S4 represents the best performing scenario out of S2 and S3a-p. Table 5 depicts the data input for running the scenarios. Due to the potential inaccuracy in inventory records and multiple adjustments (e.g. shrinkage or expiration) in the empirical data (as discussed by Chen and Mersereau, 2015), we use the first recorded inventory level within the testing period for each product. Based on this, we compute changes to inventories according to demand, supply and shelf life. The FFP processor fill-rate is the mean value from September 1, 2019, to October 31 2019.

Table 5: Data input for the different scenarios

Data input	**S2**	**S3a/../p**	**S4**
Empirical store orders	*x*		*x*
Empirical FFP processor fill-rate	*x*	*x*	*x*
Calculated inventory level	*x*	*x*	*x*
Order-based store demand forecast	*x*		*x*
Order-based wholesaler demand forecast	*x*		*x*
POS-based store demand forecast		*x*	*x*
POS-based wholesaler demand forecast		*x*	*x*
Processing information	*x*	*x*	*x*

Figure 4 shows the computation model for the different scenarios, with each step explained in the following. The model is iterative and runs 61 times for each FFP.

Figure 4: Computation model for information sharing



Steps 1-2: Update and aggregate the POS data (Wholesaler or Retail Store)
Scenario S2: at time-point t the historical store orders SO from retail store r for product p are updated until the last registered store order (equation 1). Then, aggregated for all retail stores $RS_1 \rightarrow RS_x$:

$$y_{t,p}^{2} = \sum_{r=1}^{RS_1 \rightarrow RS_x} SO_{r,t,p} \tag{1}$$

Scenario S3a-p: the FFPs are scanned and sold in the retail store r in real-time. At time-point t the real-time POS data POS for product p is collected from cash registers (equation 2). Then, updated and aggregated for all retail stores $RS_1 \rightarrow RS_x$:

$$y_{t,p}^{3_{a \rightarrow p}} = \sum_{r=1}^{RS_1 \rightarrow RS_x} POS_{r,t,p} \tag{2}$$

Step 3: Forecast demand for the following day (Wholesaler)
Different forecasting models are used in the retail context, depending on, e.g. if the demand is normal, seasonal or campaign (e.g. Bojer et al., 2019; Fildes et al., 2018). Using the POS data, we choose the autoregressive moving average (ARIMA) (2017). Since the POS data shows strong correlation across weekdays and is impacted by campaigns and inventory levels, we choose the seasonal SARIMA (p, d, q, P, D, Q)m. Four external regressors are used: inventory level, weekday of forecasting, type of campaign and the day of the campaign. Since empirical demand data for one year is available, we cross-validate the forecasting models across a training set (in-sample) and a test set (out-of-sample) (Kourentzes et al., 2020). The out-of-sample set is the 61 days with detailed POS data i.e. real-time testing period. Following Ehrenthal et al. (2014), we investigate for inter- or intra-day correlation in POS data across the cumulative percentage of total sales each day of the week. The POS data correlates across weekdays, and S-curves are fitted to each weekday's median sales for use in the forecasting. We select a median-based approach since a mean-based entails normally distributed demand (Aczel and Sounderpandian, 2009) which is not the case here. The statistical programming language R (package: **smooth**) is used to compute the forecasts. R automatically optimises the models for their different parameters. The forecasting model encompassing both normal and campaign demand was run across all 50 products,17 scenarios (excluding S4) and 61 days during the testing period, in total 51,850 model runs.

Often used forecasting accuracy measures in retail include "mean error" (ME), "mean absolute percentage error" (MAPE) and "root mean squared error" (RMSE) (Gneiting, 2011; Priyadarshi et al., 2019; Ramos et al., 2015). We use weighted versions, so that, e.g. for MAPE while "the classical (M)APE sets absolute errors in relation to the actual values, the w(M)APE considers percentage errors and again weighs them by actual values" (Kolassa and Schütz, 2007, p. 41). To avoid situations where two different time-points may have the same error-value, we use a hierarchy with three accuracy measures. If perform equally well at the first measure, then evaluate according to the second, and so forth. The formulation and hierarchy of the errors used in this study is: wMAPE (first, equation 1), wRMSE (equation 4) and wME (equation 5). The accuracy measures are formulated as follows, where y_(t,p) is actual demand at time t for product p, and y^_(t,p) the forecasted demand.

$$\mathrm{wMAPE_p} = \frac{\frac{1}{n}\sum_{t=1}^{n}|y_{t,p} - \hat{y}_{t,p}|}{\frac{1}{n}\sum_{t=1}^{n}(y_{t,p})} \tag{3}$$

$$\mathrm{wRMSE_p} = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_{t,p} - \hat{y}_{t,p})^2}}{\frac{1}{n}\sum_{t=1}^{n}(y_{t,p})} \tag{4}$$

$$\mathrm{wME_p} = \frac{\frac{1}{n}\sum_{t=1}^{n}(y_{t,p} - \hat{y}_{t,p})}{\frac{1}{n}\sum_{t=1}^{n}(y_{t,p})} \tag{5}$$

Step 4: Inventory coverage (Wholesaler)
Based on updated inventory level, it is evaluated if there is enough in inventory to satisfy the day's demand after subtracting products exceeding their shelf life. If meeting the demand, no or-der is created, and the computation ends in step eight. If not meeting the demand, the process continues to step five. Safety stocks are not used – inventories come from over-forecasting the previous period(s). An algorithm was created and written in R to evaluate while considering shelf life, i.e. product deteriorates. The full R-code can be provided by the authors upon request.

Step 5: Calculate order-size and send order
The order-size follows the order-up-to level (OUL) approach. Since FFPs are ordered and delivered to the wholesaler daily, we consider the OUL for product p at time t equivalent to forecasted demand at time t, $OUL_t = \hat{y}_{t,p}$. Since calculating according to forecast, rather than mean demand, a buffer is included in the forecasted demand $\hat{y}_{t,p}$. The order size is either equivalent to the forecasted demand (i.e. $OUL_{t,p}$) minus the beginning inventory from time t, $I_{beginning,t,p}$ or zero. The beginning inventory is yesterday's ending inventory minus expired products δ_t (equation 6). In this study we consider $I_{beginning,t,p} = I_{ending,t-1,p} - \delta_{t,p}$.

$$\mathrm{Q_{ordered,t,p}} = \begin{cases} \mathrm{OUL_{t,p} - I_{beginning,t,p}} & , \quad \text{if } \hat{y}_{t,p} > \mathrm{I_{beginning,t,p}} \\ 0 & , \quad \text{if } \hat{y}_{t,p} \leq \mathrm{I_{beginning,t,p}} \end{cases} \tag{6}$$

Steps 6-7: Receive order and evaluate against max/min-limits (FFP Processor)
The order-size $\mathrm{Q_{ordered}}$ is evaluated according against max-min allowed deviations i.e. processing information. Depending on if the order-size is within/outside the max/min-limits, the order is accepted or adjusted. The evaluation is according to the actual ordered amounts in scenario 1 and the

allowed deviation from actual processing information (equation 7). The min-level is ordering zero FFPs. The historical fill-rate *FR* is also included. Thus, the delivered order-size at wholesaler $Q_{delivered}$ is:

$$\mathrm{Q_{delivered,t,p}} = \begin{cases} \mathrm{Q_{ordered,t,p} * FR_p} & , \quad \text{if } 0 < \mathrm{Q_{ordered,t,p}} < \mathrm{Q_{max,t,p}} \\ \mathrm{Q_{max,t,p} * FR_p} & , \quad \text{if } 0 < \mathrm{Q_{max,t,p}} < \mathrm{Q_{ordered,t,p}} \end{cases} \tag{7}$$

Step 8: Ending computation

The computation ends and update the daily information archives throughout the model. The next model then runs again 60 times (i.e. two months period, followed by 61 new computations for the different demand types. When complete, the next product is computed, until all FFPs are computed.

After running the computation for scenario S2 and S3a-p, scenario S4 is run. Here, the best performing scenario from S2 and S3a-p is chosen, thereby differentiating the information sharing according to best forecasting performance at product level. Table 6 illustrates how the 50 FFPs distribute across the time-points for real-time sharing (S3a-p) and using historical order (S2). All FFPs but one was chosen based on wMAPE. While 38% of FFPs perform best when not sharing POS-based information, 62% of the FFPs perform best when sharing.

Table 6: Number of products per scenario for information sharing

S2 - order	S3a - 08:00	S3b - 09:00	S3c - 10:00	S3d - 11:00	S3e - 12:00	S3f - 13:00	S3g - 14:00	S3h - 15:00	S3i - 16:00	S3j - 17:00	S3k - 18:00	S3l - 19:00	S3m - 20:00	S3n - 21:00	S3o - 22:00	S3p - 23:00	S4 – diff.
19	*5*	*3*	*4*	-	-	-	*2*	*1*	*1*	*2*	*3*	*1*	-	*4*	*1*	*3*	*49*

3.4. Evaluating the sharing scenarios

Four performance measures evaluate the effect: (equation 8) fill-rate FR from FFP processor to wholesaler (Huber et al., 2017) – the percentage of FFPs delivered out of ordered; (equation 9) inventory days at the wholesaler ID – the number of days the FFP is in inventory; (equation 10) average inventory level at the wholesaler AIL – the mean value of inventories at the end of each day; (equation 11) waste in inventory from over-forecast at the wholesaler W – the sum of FFPs from OUL which cannot be absorbed by the following days' shelf life demand.

$$FR_p = \begin{cases} 100 & , \quad if\ 0 < Q_{ordered,t,p} = Q_{delivered,t,p} \\ \frac{1}{n}\sum_{t=1}^{n} \frac{Q_{delivered,t,p}}{Q_{ordered,t,p}} * 100 & , \quad if\ 0 < Q_{delivered,t,p} < Q_{ordered,t,p} \end{cases} \tag{8}$$

$$ID_p = \frac{\sum Q_{delivered,p}}{AIL_p} \quad (9)$$

$$AIL_p = \frac{1}{n}\sum_{t=1}^{n}\left(max\left(I_{beginning,t,p}, OUL_{t,p}\right) - Q_{store,t,p}\right) \quad (10)$$

$$W_p = \sum_{t=OUL_t > \sum_{T=t}^{T+S}\hat{y}_{t,p}}^{n}\left(OUL_{t,p} - \sum_{T=t}^{T+S}\hat{y}_{t,p}\right) \quad (11)$$

We evaluate scenario S2, S3a/../p and S4 in terms of normal and campaign demand, i.e. 109,800 specific scenarios (50 FFPs *18 scenarios * 2 demand types * 61 days). Each is evaluated by the four performance measures, i.e. 439,200 results. We assume that the performance *across* the 50 FFPs (which *individually* is calculated as median performance) is normally distributed, and thus calculate mean performance.

4. Results

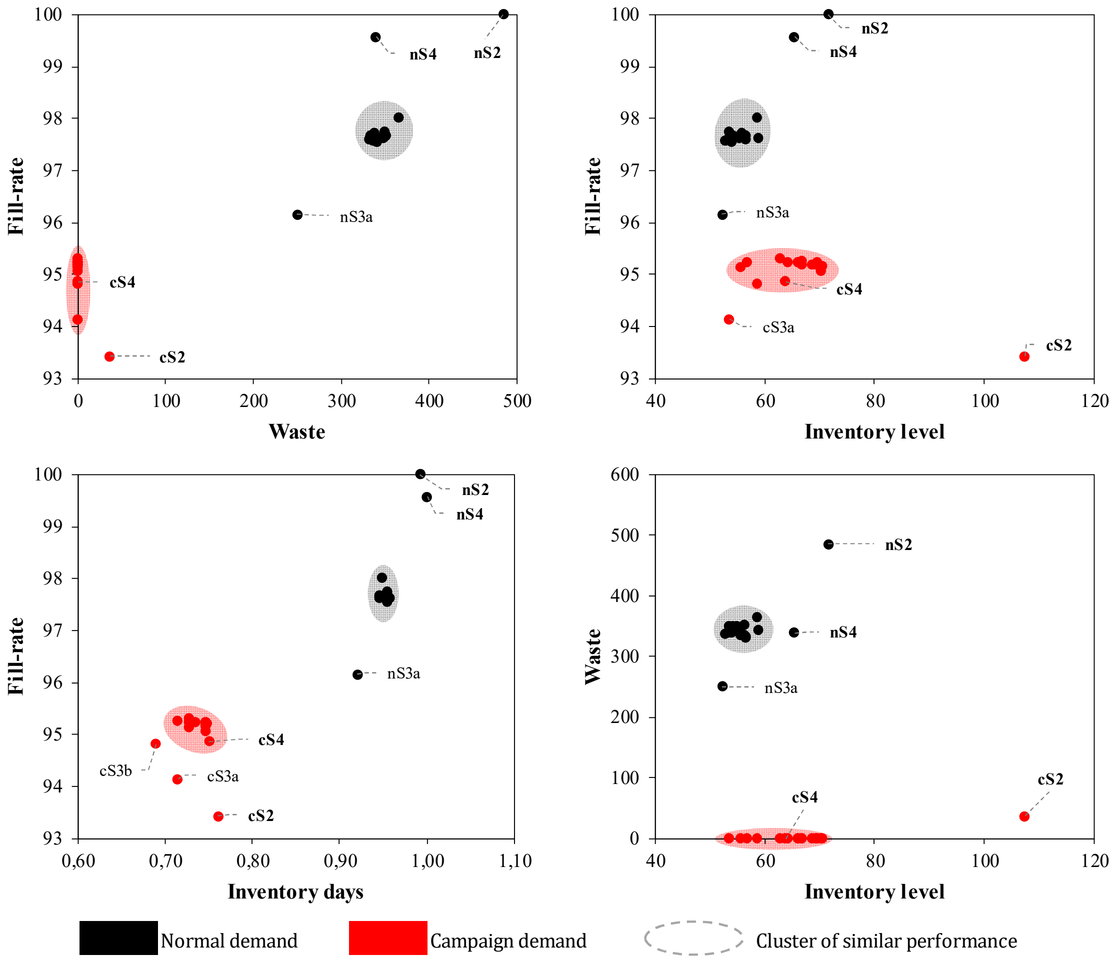
This section presents the results of the effect of the different scenarios' information sharing on the fill rate, inventory days and waste. First, the effect for normal and campaign demand is summa-rized. Next, we analyse the results in terms of processing method. The section ends with a discus-sion and confirmation/rejection of the research hypotheses. A detailed overview of the effect from the different scenarios on each performance measure is provided in Appendix 1.

4.1. H1a, H1b, H2a and H2b: Information sharing for campaign and normal demand

Figure 6 summarises the effect on each of the scenarios S2, S3a/../p (H1a and H1b) and S4 (H2a and H2b), respectively. Normal demand is represented with black, and the campaign with red colour in the figure. Starting with the upper left graph, normal demand generally has higher fill-rate than campaign demand, but higher waste levels. For normal demand, the order-based scenario (nS2) has 100% fill-rate, yet it is only 0.4% higher than the differentiated scenario (nS4) and causes 42% higher waste level. For pure real-time scenarios (nS3a/../p), most waste levels are similar to nS4, and a tendency of around 2% lower fill-rate, and up to 3.8% for nS3a. For campaign demand, the order-based scenario (cS2) results in the lowest fill-rate and highest waste level. In fact, comparing to cS3a/../p and cS4, all scenarios but cS2 have no waste levels. While the differentiated scenario for normal demand (nS4) has better fill-rate than real-time (nS3a/../p), then for campaign demand real-time sharing at 16:00 (cS3i) provides the highest fill-rate with cS4 is at 94,9%. Thus, for normal demand, the differentiated nS4 has the best performance, while for campaign demand it is the real-time cS3i. For fill-rate and inventory level (upper right graph), both normal and campaign demand tend to have similar inventory levels mainly within a 20 units range. For normal demand specifically, both nS3a/../p and nS4 have lower inventory levels than order-based nS2, nS3a/../p clustering within a 7 units range. For campaign demand, cS2 generally has around 70% higher inventory level than nS3a/../p and nS4. Comparing fill rate and inventory days (lower left graph), campaign demand generally entails lower number of inventory days than normal demand. However, they all have less than one inventory day, and thus not considered any further. Comparing waste-levels against inventory levels (lower right graph), campaign demand performs better than normal with waste level, while in terms of inventory levels normal and campaign demand perform similarly, except for cS2.

For all comparisons (i.e. entire Figure 6), we conclude that for both normal and campaign demand respectively real-time sharing tend to have same performance regardless of the time-point of sharing. While normal demand entails the highest fill-rates, campaign demand entails the lowest waste. One reason for this is the differences in terms of demand variation and periods versus demand level. Campaign demand has a negative effect on the fill-rate due to the limited period in which the campaign runs and the demand variation in POS and orders, limited processor capacity at FFP processor to follow fluctuations in demand and inaccurate demand forecasting at wholesaler. However, despite this the generally higher demand-level reduces the impact from over-forecasting causing waste, since the inventory built up gets absorbed by the following day's demand following the FIFO-principle. Oppositely for normal demand, the relatively more stable and continuous demand reflects the latent improvement in forecasting and thus fill-rate. However, the generally lower demand level makes normal demand more sensitive to waste from any forecasting and ordering inaccuracy caused by e.g. demand fluctuation or periods with no demand. Further, when a campaign ends, any remaining inventory switch to inventory during normal campaign, and hence any inventory pushed through the campaign period may cause waste in the normal period. Thus, we *reject* hypothesis H1a, that real-time sharing has a positive effect on the performance compared to order-based sharing for normal demand. Although waste, inventory level and inventory days improve, the differences in these are not considered to outweigh the up to 2.5% lower fill-rate (excluding nS3a). We *accept* hypothesis H1b, that real-time sharing has a positive effect on performance compared to order-based sharing during campaign demand, since all real-time scenarios entail improved performance across all measures compared to order-based information (cS2). We *accept* hypothesis H2a, that differentiated sharing *improves* the effect on performance for normal demand compared to order-based and real-time sharing. Although a marginal lower fill-rate (to nS2), nS4 leads to the relative best performance across all scenarios and increase the fill-rate for real-time sharing. We *reject* hypothesis H2b, that differentiated sharing *improves* the effect on performance for campaign demand compared to order-based and real-time sharing. Although performing better than cS4, then comparing to real-time sharing the performance is similar or even lower.

Figure 6: Mean value of median performance, campaign/normal demand (H1a, H1b, H2a and H2b)



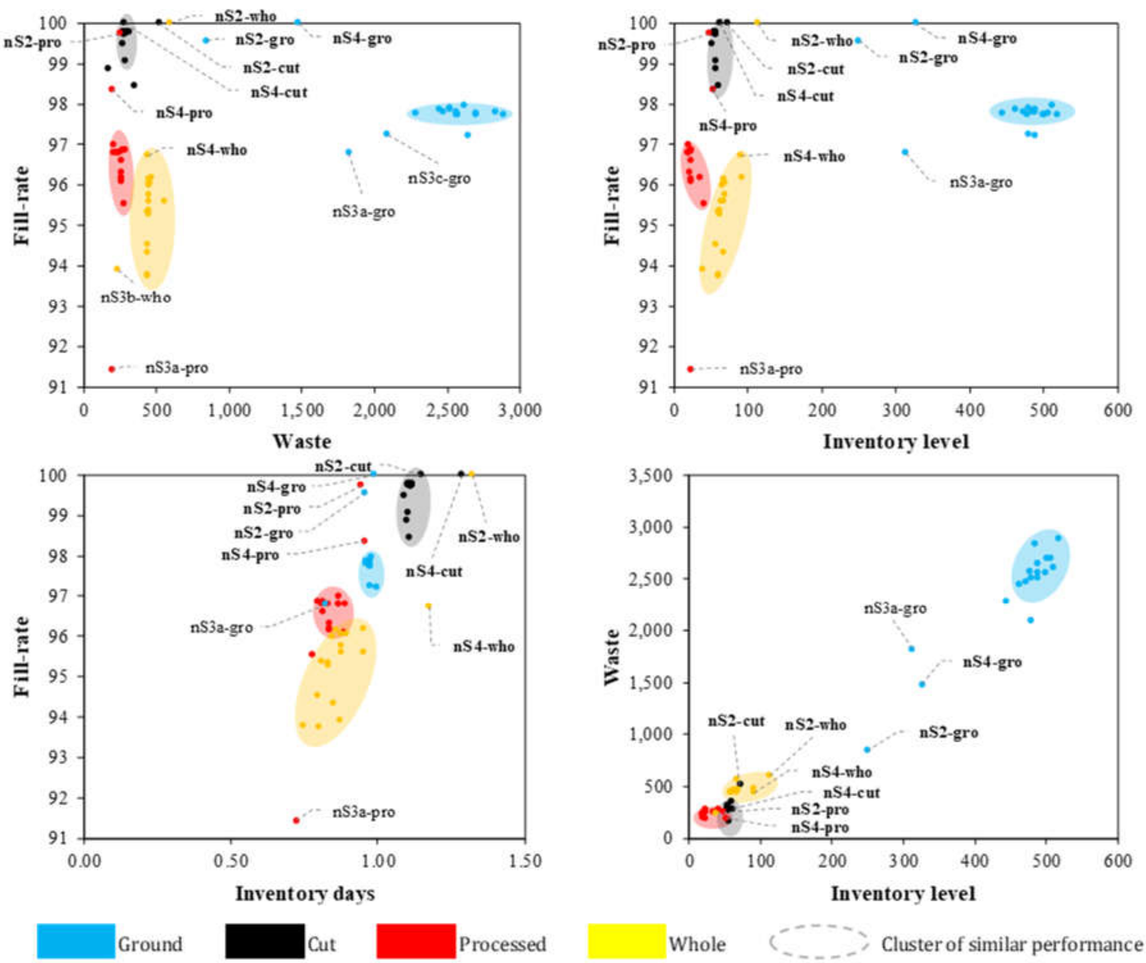
4.2. H3a, H3b, H4a and H4b: Information sharing for campaign and normal demand, considering processing method

Figure 8 and 9 summarise the effect for S2, S3a/../p and S4 on respectively normal and campaign demand grouped by processing method. Starting with Figure 8 and normal demand (upper left graph), the processing methods tend to have similar performance, while Cut FFPs entail the high-est fill-rate and Ground FFPs the most waste. Whole and Processed FFPs have similar perfor-mance. Specifically, order-based sharing entail up to 3.5% higher fill-rate for Processed (nS2-pro), Ground (nS2-gro) and Whole (nS2-who) FFPs, while for Cut FFPs the differentiated sharing (nS4-cut) performs better. Pure real-time sharing entails up to more than 8% lower fill-rate (nS3a-pro). The Cut, Processed and Whole

FPPs entail the lowest waste when differentiating sharing (nS4-cut, nS4-pro and nS4-who), while the Ground FFPs entail the lowest waste when order-based sharing (nS2-gro). In terms of inventory level (upper right graph), the Processed and Ground FFPs perform better when order-based sharing (nS2-pro and nS2-gro) while Cut and Whole FFPs per-form better when differentiated sharing (nS4-cut and nS4-who). The real-time sharing entails more than 28 times higher inventory level comparing best- and worst-performing (nS3m-gro vs nS3l-pro). For inventory days (lower left graph), all real-time scenarios (but for Cut FFPs) entail less than one day in inventory. For Cut and Whole FFPs, both order-based and differentiated shar-ing entails more than one day in inventory (i.e. nS2-cut, nS4-cut, nS2-who and nS4-who). Com-paring inventory level and waste (lower right graph), in particular, Processed and Cut FFPs have similar performance, while Whole FFPs entail slightly higher waste and inventory. Ground FFPs perform worst.

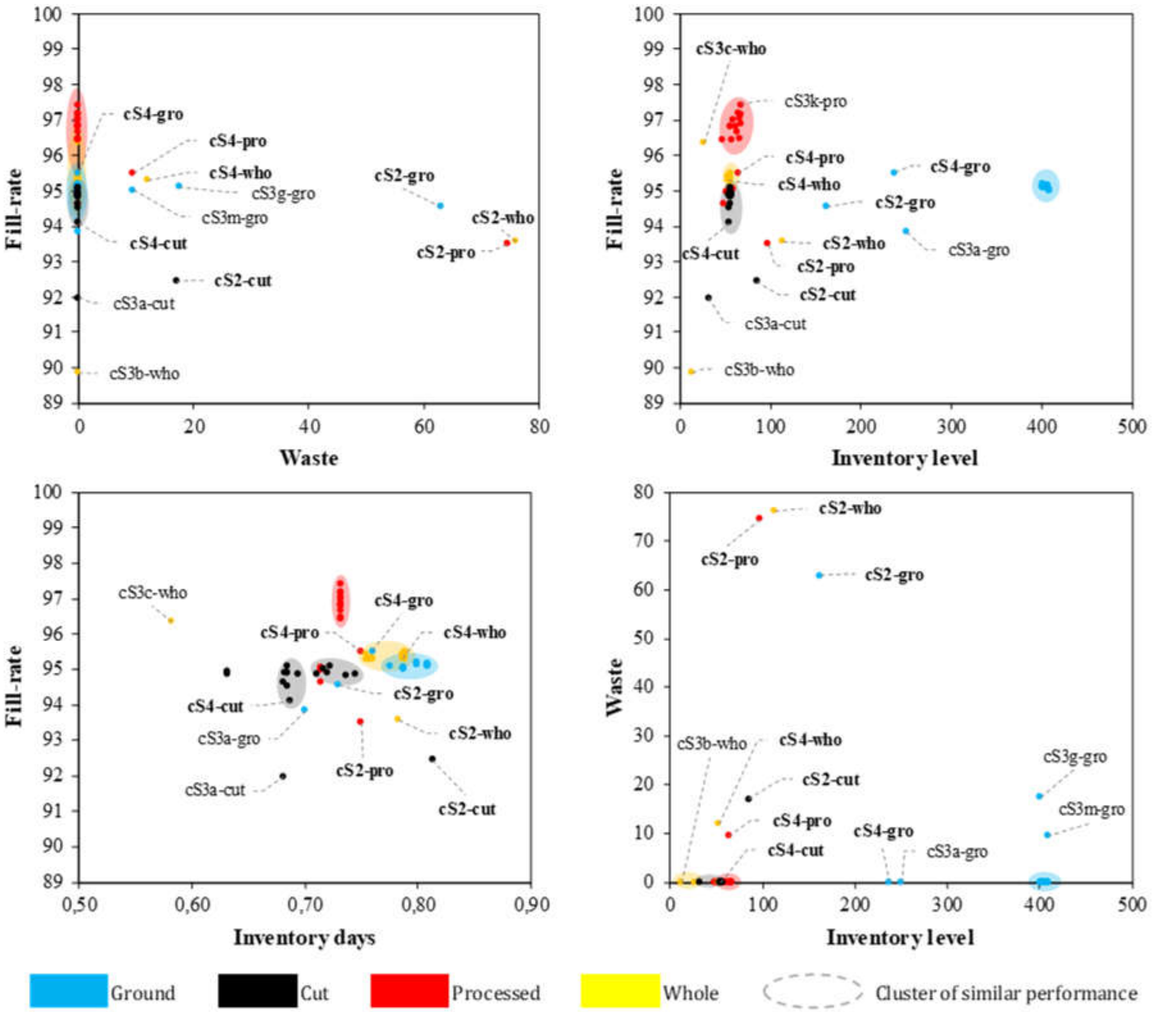
For all comparisons (i.e. entire Figure 8), the FFPs tend to be similar within processing meth-ods, with Cut FFPs generally having the best performance. The Whole and Processed FFPs tend to have relatively similar performance, while Ground FFPs have the lowest performance. One reason for the higher waste for Ground FFPs is the demand level and the impact from excessive inventory when a campaign period ends and demand switch to normal, combined with the generally larger demand for Ground FFPs compared to other types. The nS2-pro, nS2-who, nS2-gro and nS4-cut collectively have the best performance. Thus, we accept H3a, that processing-differentiated real-time sharing has a positive effect on performance compared to order-based sharing for normal demand, since allowing differentiation between order-based and real-time sharing across pro-cessing methods. Although the effect is negative for whole, Ground and Processed FFPs, it is positive for Cut FFPs. In this way, since mere real-time sharing also induced a negative impact, then not considering processing methods would not allow the understanding of Cut FFPs benefitting from differentiated sharing. We accept H4a, that processing-differentiated and time-differentiated sharing improves the effect on performance compared to order-based and real-time sharing for normal demand. While the effect compared to order-based sharing reflects H3a (i.e. positive ef-fect for Cut, but negative effect for whole, Ground and Processed), then the effect compared to real-time sharing is positive for all processing methods.

Figure 8: Mean value of median performance, normal demand with processing method (H3a and H4a)



For Figure 9 and campaign demand (upper left graph), almost all real-time scenarios for the different processing methods have no waste, only differing up to almost 5% in fill-rate. Although the differentiated sharing performs better than order-based sharing in terms of waste, the real-time scenario performs even better for cS4-pro and cS4-who. In particular for order-based sharing for Ground (cS2-gro), Whole (cS2-who) and Processed (cS2-pro) FFPs the waste-levels are significantly higher than any other scenario. Two real-time scenarios (cS3a-cut and cS3b-who) entail significantly lower fill-rate, although no waste. In terms of inventory level (upper right graph), Cut, Processed and Whole are in the same range of inventory, while Ground FFPs entail up to 26 times higher inventory (S3m-gro vs S3e-pro). The differentiated sharing has lowest inventory for Processed (cS4-pro), Cut (cS4-cut) and Whole (cS4-who) FFPs while order-based sharing performs best for Ground FFPs (cS2-gro). The Ground FFPs have the largest deviation in performances. For inventory days (lower left graph), all scenarios entail less than one day in inventory, and hence since all FFPs have less than one day in inventory, this is not considered any further. Comparing inventory level and waste (lower right graph), all real-time sharing cluster around the same performance, while order-based and differentiated sharing mostly entail relatively higher waste and/or inventory level. Ground FFPs perform worst.

Figure 9: Mean value of median performance, campaign demand with processing method (H3b and H4b)



For all comparisons (i.e. entire Figure 9), the scenarios generally results with clustering within processing methods with Processed FFPs performing best. Ground, Cut and Whole FFPs tend to have same fill-rate and majority of all scenarios entail no waste. The cS3k-pro, cS3c-who, cS3c-cut, cS4-gro collectively have the best performance entailing no waste and highest fill-rate. Thus, we *accept* H3b that processing-differentiated real-time sharing has a positive effect on performance compared to order-based sharing for campaign demand, since all real-time scenarios reduce or doesn't experience waste, while improving the fill-rate. We *reject* H4b that processing-differentiated and time-differentiated sharing improves the effect on performance compared to order-based and real-time sharing for campaign demand, since pure real-time sharing entail better performance across all processing methods but for Ground FFPs.

Thus, four hypotheses are accepted and four rejected as depicted in Table 7.

Table 7: Confirmation/Rejection research hypotheses

	Normal demand	**Campaign demand**
Not considering processing method	↗ H1a *(real-time)* **REJECTED** ↑ H2a *(differentiated)* **ACCEPTED**	↗ H1b *(real-time)* **ACCEPTED** ↑ H2b *(differentiated)* **REJECTED**
Considering processing method	↗ H3a *(real-time)* **ACCEPTED** ↑ H4a *(differentiated)* **REJECTED**	↗ H3b *(real-time)* **ACCEPTED** ↑ H4b *(differentiated)* **REJECTED**

4.3. Sensitivity analysis of results

In addition, a sensitivity test was carried out across the different demand type and processing method combinations to investigate the robustness of the performance results. Table 8 depicts the results, with different levels of importance given to fill-rate and waste-level performance, considering both best and worst performance. For the best performance, differentiated information sharing mostly performs best regardless of whether the focus is on fill-rate or waste-level. For campaign demand, real-time sharing tend to outperform the differentiated sharing, even when considering the processing method, then for Cut, Processed and Whole FFPs, real-time sharing at one single time point entails best performance. For Ground FFPs, the differentiated sharing entails best performance. When waste is most important, real-time sharing at specified time-point for all products is best for both normal and campaign demand, while differentiated sharing is entailed for campaign demand (ground and Whole FFPs) and normal demand (processed FFPs). For normal demand Ground FFPs order-based sharing entails best performance. When focusing on only fill-rate and waste, both order-based, real-time and differentiated sharing have the same performance for normal demand in general (i.e. not considering processing methods) and for normal demand Ground products. The results indicate that order-based sharing consistently entail worst performance for campaign demand, regardless the consideration of processing methods. Also, that differentiated sharing generally tend to benefit normal demand, while real-time sharing benefit campaign demand – with the exception of Ground products.

Table 8: Sensitivity test of performance across demand type and processing method

		Best scenario performance			Worst scenario performance		
Demand type	**Processing method**	Score: 2*FR + 1*Waste	Score: 1*FR + 1*Waste	Score: 1*FR + 2*Waste	Score: 2*FR + 1*Waste	Score: 1*FR + 1*Waste	Score: 1*FR + 2*Waste
Normal	-	*nS4*	*nS2/nS3a/nS4*	*nS3m*	*nS3j*	*nS3j*	*nS3f*
Campaign	-	*cS3e*	*cS3e*	*cS3e*	*cS2*	*cS2*	*cS2*
Normal	Cut	*nS4-cut*	*nS4-cut*	*nS3k-cut*	*nS3b-cut*	*nS3b-cut*	*nS3b-cut*
Campaign	Cut	*cS3c-cut*	*cS3c-cut*	*cS3c-cut*	*cS2-cut*	*cS2-cut*	*cS2-cut*
Normal	Ground	*nS4-gro*	*nS2/nS4-gro*	*nS2-gro*	*nS3b/m-gro*	*nS3m-gro*	*nS3m-gro*
Campaign	Ground	*cS4-gro*	*cS4-gro*	*cS4-gro*	*cS2-gro*	*cS2-gro*	*cS2-gro*
Normal	Processed	*nS4-pro*	*nS4-pro*	*nS4-pro*	*nS3b-pro*	*nS3b-pro*	*nS3b-pro*
Campaign	Processed	*cS3k-pro*	*cS3k-pro*	*cS3k-pro*	*cS2-pro*	*cS2-pro*	*cS2-pro*
Normal	Whole	*nS4-who*	*nS4-who*	*nS4-who*	*nS3e-who*	*nS3c-who*	*nS3c-who*
Campaign	Whole	*cS3c-who*	*cS3c-who*	*cS3c-who*	*cS2-who*	*cS2-who*	*cS2-who*

Note: yellow = differentiated information sharing, blue = order-based information sharing, green = same performance

5. Discussion

This study shows that pure real-time POS-based demand information sharing (at one time-point) has a positive effect on waste, inventory days and inventory level generally and a positive impact on fill-rate for campaign demand. However, there is a decrease in fill-rate for normal demand. A reason for this may be found in the intra-day correlation in POS data across the week as discussed by Ehrenthal et al. (2014). The weekdays tend to have the same demand patters with a lag of seven (e.g. Mondays tend to have one S-curve, Tuesdays another etc.). Thus, the real-time sharing at different time-points throughout the day provides latest demand signal from market and "allows to capture the latest demand fluctuations and "base the order on the actual sales" (Kaipia et al., 2013, p. 272). This improves the forecasted demand to expect, and these results implicitly extend the findings from Fransoo and Wouters (2000) in that the POS data (in this case real-time POS-based) has a positive effect on fill-rate and freshness (i.e. inventory days and inventory level) for campaign demand. Although, it should be noted that this improvement does not counterbalance the impact from excessive inventory at the end of campaign periods (causing reduced performance in particular due to waste).

Differentiating the information sharing at the product level, i.e. both order-based and real-time sharing (at different time points) entails the best performance at an overall level. Although the fill-rate is marginally (!) lower (for normal demand), particularly the waste-level is largely im-proved in general. In terms of inventory days and inventory levels, pure real-time sharing may, in some instances entail better performance. These results seem to confirm Narayanan et al. (2019) and Williams and Waller (2010) in that POS data in forecasting has a positive effect on order-sizing. However, since this study relies on a franchise-based retail chain, the findings seem to contradict Fransoo and Wouters (2000) about the effect of POS data in a franchise context (with local trade-offs). However, it should be noted that this study assesses performance at the wholesaler level. Thus store-individual trade-offs may balance one another out (due to aggregation).

Planning environment characteristics are widely recognised to have an impact on processing planning and control (Entrup, 2005; Romsdal et al., 2014; Spenhoff et al., 2014; Wänström and Jonsson, 2006) and sales and operations planning (Dreyer et al., 2018; Ivert et al., 2015), e.g. de-mand volume and demand variation. However, no studies were found to investigate this in relation to real-time POS-based information sharing. This study considers processing methods (as depicted in Figure 5) as an umbrella terms and computes the effects on grouping products according to pro-cessing method. In overall, Ground FFPs performed most different from the other processing methods which were mainly differing in fill-rate. Considering real-time POS-based information with product groupings, the reduced fill-rate and, for Ground FFPs, the waste, does not entail an improved performance, rather lower performance. However, it should be noted that by grouping according to processing methods, it is found that real-time sharing for Cut FFPs with normal de-mand has a positive effect compared to order-based sharing. This raise notion to the current grouping of products in studies, i.e. only according to demand type, in that the consideration of more/other product characteristics may allow a more nuanced understanding of when (real-time) POS-based information sharing is beneficial. Further, considering the multiple planning environ-ment characteristics reported in literature, grouping at parallel levels may also provide information about the effect of order-based and real-time information sharing. As example, grouping according to e.g. demand variation may entail deeper insight into the effect, considering that real-time POS-based information sharing may/may not provide a different picture given the latent in-creased uncertainty. Also, it is interesting that while the product-process matrix in Figure 5 entails lower demand for Ground FFPs due to the increased processing steps, the data indicated that Ground FFPs were in fact product with largest demand followed by Cut FFPs, and not Whole FFPs. This indicates that there may be value in including more planning environment characteristics when deciding on information sharing in real-life.

Although, the in-sample period used for testing the computation model was 10 months aggregated POS data, this study uses a rather small focused sample (two months detailed POS data 50 FFPs) compared to other studies using up to 1000 products (Ehrenthal et al., 2014) or up to two years daily POS data (Narayanan et al., 2019). However, aside from providing information about two different demand types, then also given the focus on real-time sharing i.e. 18 different scenarios, the time-period is considered suitable. Also, e.g. Williams and Waller (2011) used 13 weeks out-of-sample period. Further, certain uncertainty must be attained to the fact that other studies covering e.g. one year include seasonal fluctuations. Also, while studies on e.g. non-perishable products tend to allow backlogs when computing, this study considered demand which cannot be satisfied due to, e.g. not in production or already Processed as lost sales. Lastly, computational setup may be different from other studies, e.g. in this study, then after the FFPs are processed, they are delivered to wholesaler and inventory levels are updated accordingly. Also, no transportation/capacity limitations/restrictions are included when ordering from FFP processors.

Overall, this study extends current literature (Table 1) by providing new empirical information and results from a holistic point of view on RP&C (combining forecasting and inventory control). Namely how timing and real-time POS data may improve performance, as well as other performance improvement measures e.g. waste. Current studies consider either forecasting or inventory control and mainly focus on week-level decision-horizon, while this study considers daily. The study adds to current literature streams on POS data/-based information sharing in the supply chain in terms of both inventory/order decision-making (e.g. Croson and Donohue, 2003; Ehrenthal et al., 2014; Williams et al., 2014) and demand forecasting (e.g. Hartzel and Wood, 2017; Jonsson and Mattsson, 2013; Williams and Waller, 2010). Both by providing empirical evidence on the context of FFPs and by considering different demand types and processing methods. Specifically, this study also adds to the current conceptual modelling of centralised forecasting (Alftan et al., 2015) by empirically testing the effect on different performance measures. Overall, this study adds to the current literature by being the first study specifically focusing on real-time sharing through a product level scope. Another delimitation in this project is the comparison of effect. This study focuses predominantly on comparing the performance across processing meth-ods, rather than the within processing methods. This allows understanding of whether a known FFP wholesaler-grouping of products indicates any different effect and if so, to what level. It does not consider why one scenario performs better than another and what is the cause. Instead, the results identify which information scenario within a processing method is best, and how is this different from another processing method (inter-effect). By differentiating at this more detailed lev-el, a new dimension is added for when researching POS data and real-time information sharing.

6. Conclusion & Future Research Directions

This paper tests the effect of real-time POS-based demand information sharing between wholesaler and FFP processor during RP&C in different demand situations and for different processing methods. A large empirical dataset and one year's POS data for 50 FFPs is used to analyse the effect on fill-rate, inventory level, inventory days and waste-levels in demand situations. Some papers have investigated the effect of POS data on either demand forecasting or inventory control for grocery products. No found study has looked at the timing and effect of real-time POS-based information sharing at a product level, when considering both normal and campaign demand as well as the processing method.

This study identifies the effect of real-time POS data by comparing an order-based information sharing scenario against different real-time POS-based information sharing scenarios. It was found that generally real-time sharing of POS-based demand information has a positive effect on the performance, and that a reason for this is since real-time sharing utilises the S-curve to pro-vide an updated demand signal. It was also found that the differentiated information sharing at product level lead to a comparable enhanced performance, since searching for best performing scenario, whether order-based or real-time POS-based.

The study has certain managerial implication related to real-time sharing. In practice, supply chains may not have technological capability and/or equipment for handling this kind of information transfer. It is suggested that in such case, the use of POS data in itself should improve performance. This, since the reflection of actual demand, seem particular beneficial when having daily deliveries of products with very short shelf life. However, it should be noted that this study has focused on real-time sharing, deriving that similar results may not necessarily be achieved when using of historical POS data. Also, the ability to manage the information sharing at a prod-uct level with some products entailing historical order-based information sharing and other real-time POS-based information sharing may require high (cost and resource) investments across the entire supply chain, due to the high level of differentiation. In practice, it may be beneficial to start by selecting those products which are particularly sensitive (e.g. expensive of very short shelf life) or very important for the assortment. Then later expand the selection as both on-hands knowledge and (potentially) investment in IT equipment expands. Alternatively, the sharing of centralised forecasting is generally expected to bring a positive effect on the performance.

Despite 50 products were selected, and two months detailed POS data was used for detailed investigation, the study has certain limitations. In general, the two months period (September and October) may reflect a relatively more appropriate time period for such information sharing, as opposed to, e.g. Christmas, Easter, Summer or alike where the demand is even more fluctuating and demand signal potentially disrupted. However, the data set is too limited in terms of consider-ing demand cycles, seasonality and impact from campaigns. The short period also prevented significance testing since limited amount of data. This study also didn’t consider long vs short campaigns, which may lead to a different performance, e.g. one-week vs three-day campaign. Also, planning environment characteristics at FFP level were not considered from a processor point of view, but rather wholesaler RP&C point of view. This may have prevented a deeper understanding and more detailed grouping of products rather than current four groups. Also, the specific selection of beef, pork, chicken and fish products may limit the scope of potential effect, since these products are facing largest demand as opposed to other niche-products, e.g. reindeer meat, wild meat or exotic meat. These entail a latent premise for the effect that similar conditions must be fulfilled. Further, the study fundamentally relies on the selection of the 50 most demanded products, meaning less demanded, rarely ordered or more unique products have been left out, i.e. different premise for effect. Considered as a delimitation, it is worth point out the computing of empirical data rather than simulation or analytical approach. Although e.g. simulation would entail greater understanding of e.g. sensitivity of results, the empirical data allows a direct 1:1 relation to real-life situation, since the computation reflects directly the consequence if one of the scenarios would have been applied.

For future research, this study should be widened by encompassing more and different FFPs with similar short shelf life, such as other meat products, pastry, fresh meals, dairy and bread products to strengthen the findings on how real-time POS-based information sharing affects the performance. As an example, fresh meals are processed daily and to a greater extent influenced by, e.g. weekly buying behaviour, i.e. consumers eating fresh meals during the week but cooking during weekends. Given the suggestions in the literature on franchise-based focuses, it would also be of interest to investigate these ways of sharing information in other organisational focuses with automated order decision-making; e.g., corporate retail chains where the distribution centre decides when and how much to deliver to retail stores. Also, the detailed POS data should cover minimum one year, preferably three years to detect seasonality. This would also allow greater understanding of normal and campaign demand, as well as what is the effect of POS data around, e.g. holidays. By also including planning environment characteristics at a more detailed level from a processor point of view, a different grouping of products may entail different results. Also, this study delimits itself from the intra-effect of POS-based demand information sharing on scenario performances when considering the processing method. By comparing the individual scenario performances within e.g. Ground meat products, a future study would be able to investigate why one scenario performs better than within that processing method. This would allow to analyse and explore the cause and effect.

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References

Aastrup, J. and Kotzab, H. (2009), “Analyzing Out-Of-Stock in Independent Grocery Stores: An Empirical Study”, International Journal of Retail & Distribution Management, Vol. 37 No. 9, pp. 765–789.

Aastrup, J. and Kotzab, H. (2010), "Forty Years of Out-of-Stock Research - and Shelves are Still Empty", International Review of Retail, Distribution and Consumer Research, Vol. 20 No. 1, pp. 147–164.

Aczel, A.D. and Sounderpandian, J. (2009), Complete Business Statistics, 7th ed., McGraw-Hill, New York.

Alftan, A., Kaipia, R., Loikkanen, L. and Sepns, K. (2015), "Centralised Grocery Supply Chain Planning: Improved Exception Management", International Journal of Physical Distribution & Logistics Management, Vol. 45 No. 3, pp. 237–259.

Aviv, Y. (2007), "On the Benefits of Collaborative Forecasting Partnerships Between Retailers and Manufacturers", Management Science, Vol. 53 No. 5, pp. 777–794.

Barratt, M., Choi, T.Y. and Li, M. (2011), "Qualitative Case Studies in Operations Management: Trends, Research Outcomes, and Future Research Implications", Journal of Operations Management, Vol. 29 No. 4, pp. 329–342.

Bojer, C.S., Dukovska-Popovska, I., Christensen, F.M.M. and Steger-Jensen, K. (2019), "Retail Promotion Forecasting: A Comparison of Modern Approach", in Ameri, F., Stecke, K.E., Cieminski, G. von and Kiritsis, D. (Eds.), Advances in Production Management Systems, Production Management for the Factory of the Future - Proceedings Part I, Springer, pp. 575–582.

Chen, L. and Mersereau, A.J. (2015), "Analytics for Operational Visibility in the Retail Store: The Cases of Censored Demand and Inventory Record Inaccuracy", in Agrawal, N. and Smith, S. (Eds.), Retail Supply Chain Management, Quantitative Models and Empirical Studies, Springer-Verlag, New York, pp. 79–112.

Croson, R. and Donohue, K. (2003), "Impact of POS Data Sharing on Supply Chain Management: An Experimental Study", Production and Operations Management, Vol. 12 No. 1, pp. 1–11.

van Donselaar, K.H., Gaur, V., Woensel, T. Van, Rob, A.C.M., Fransoo, J.C., Donselaar, K.H. Van, Woensel, T. Van, et al. (2010), "Ordering Behavior in Retail Stores and Implications for Automated Replenishment", Management Science, Vol. 56 No. 5, pp. 766–784.

Dreyer, H.C., Kiil, K., Dukovska-Popovska, I. and Kaipia, R. (2018), "Proposals for Enhancing Tactical Planning in Grocery Retailing with S&OP", International Journal of Physical Distribution & Logistics Management, Vol. 48 No. 2, pp. 114–138.

Ehrenthal, J.C.F., Honhon, D. and Van Woensel, T. (2014), "Demand Seasonality in Retail Inventory Management", European Journal of Operational Research, Elsevier B.V., Vol. 238 No. 2, pp. 527–539.

Eisenhardt, K.M. (1989), "Building Theories from Case Study Research", Academy of Management Review, Vol. 14 No. 4, pp. 532–550.

Entrup, M.L. (2005), Advanced Planning in Fresh Food Industries, Integrating Shelf Life into Production Planning, Physica-Verlag Heidelberg, Berlin.

Eriksson, M., Strid, I. and Hansson, P.-A. (2014), “Waste of Organic and Conventional Meat and Dairy Products — A Case Study from Swedish Retail”, Resources, Conservation and Recycling, Elsevier B.V., Vol. 83, pp. 44–52.
Evans, J. (2016), “Effects of Food and Beverage Storage, Distribution, Display, and Consumer Handling on Shelf Life”, in Subramaniam, P. (Ed.), The Stability and Shelf Life of Food, 2nd ed., Woodhead Publishing, Cambridge, pp. 107–140.
Fildes, R., Ma, S. and Kolassa, S. (2018), Retail Forecasting: Research and Practice, available at:https://doi.org/10.13140/RG.2.2.17747.22565.
Flynn, B.B., Sakakibara, S., Schroeder, R.G., Bates, K.A. and Flynn, E.J. (1990), “Empirical Research Methods in Operations Management”, Journal of Operations Management, Vol. 9 No. 2, pp. 250–284.
Fransoo, J.C. and Wouters, M.J.F. (2000), “Measuring the Bullwhip Effect in the Supply Chain”, Supply Chain Management, Vol. 5 No. 2, pp. 78–89.
Gneiting, T. (2011), “Making and Evaluating Point Forecasts”, Journal of the American Statistical Association, Vol. 106 No. 494, pp. 746–762.
Hartzel, K.S. and Wood, C.A. (2017), “Factors that Affect the Improvement of Demand Forecast Accuracy through Point-of-Sale Reporting”, European Journal of Operational Research, Elsevier B.V., Vol. 260 No. 1, pp. 171–182.
Hayes, R.H. and Wheelwright, S.C. (1979), “Link Manufacturing Process and Product Life Cycles”, Harvard Business Review, Vol. 57, pp. 133–140.
Huber, J., Gossmann, A. and Stuckenschmidt, H. (2017), “Cluster-Based Hierarchical Demand Forecasting for Perishable Goods”, Expert Systems with Applications, Elsevier Ltd, Vol. 76, pp. 140–151.
Ivert, L.K., Dukovska-Popovska, I., Kaipia, R., Fredriksson, A., Dreyer, H.C., Johansson, M.I., Chabada, L., et al. (2015), “Sales and Operations Planning: Responding to the Needs of Industrial Food Producers”, Production Planning & Control, Taylor & Francis, Vol. 26 No. 4, pp. 280–295.
Jin, Y., Williams, B.D., Tokar, T. and Waller, M.A. (2015), “Forecasting With Temporally Aggregated Demand Signals in A Retail Supply Chain”, Journal of Business Logistics, Vol. 36 No. 2, pp. 199–211.
Jonsson, P. and Holmström, J. (2016), “Future of Supply Chain Planning: Closing the Gaps Between Practice and Promise”, International Journal of Physical Distribution & Logistics Management, Vol. 46 No. 1, pp. 62–81.
Jonsson, P. and Mattsson, S.-A. (2003), “The Implications of Fit between Planning Environments and Manufacturing Planning and Control Methods”, International Journal of Operations & Production Management, Vol. 23 No. 8, pp. 872–900.
Jonsson, P. and Mattsson, S.-A. (2013), “The Value of Sharing Planning Information in Supply Chains”, International Journal of Physical Distribution & Logistics Management, Vol. 43 No. 4, pp. 282–299.
Jonsson, P. and Myrelid, P. (2016), “Supply Chain Information Utilisation: Conceptualisation and Antecedents”, International Journal of Operations & Production Management, Vol. 36 No. 12, pp. 1769–1799.

Kaipia, R., Dukovska-Popovska, I. and Loikkanen, L. (2013), “Creating Sustainable Fresh Food Supply Chains through Waste Reduction”, International Journal of Physical Distribution & Logistics Management, Vol. 43 No. 3, pp. 262–276.

Kaipia, R., Korhonen, H. and Hartiala, H. (2006), “Planning Nervousness in a Demand Supply Network: An Empirical Study”, The International Journal of Logistics Management, Vol. 17 No. 1, pp. 95–113.

Kembro, J. and Selviaridis, K. (2015), “Exploring Information Sharing in the Extended Supply Chain: An Interdependence Perspective”, Supply Chain Management, Vol. 20 No. 4, pp. 455–470.

Kolassa, S. and Schütz, W. (2007), “Advantages of the MAD/Mean Ratio over the MAPE”, Foresight: The International Journal of Applied Forecasting, No. 6, pp. 40–43.

Kourentzes, N., Trapero, J.R. and Barrow, D.K. (2020), “Optimising Forecasting Models for Inventory Planning”, International Journal of Production Economics, Elsevier B.V., No. In press, pp. xx–xx.

Kuhn, H. and Sternbeck, M.G. (2013), “Integrative retail logistics: An exploratory study”, Operations Management Research, Vol. 6 No. 1–2, pp. 2–18.

Mena, C., Adenso-Diaz, B. and Yurt, O. (2011), “The Causes of Food Waste in the Supplier-Retailer Interface: Evidences from the UK and Spain”, Resources, Conservation and Recycling, Elsevier B.V., Vol. 55 No. 6, pp. 648–658.

Mena, C., Terry, L.A., Williams, A. and Ellram, L.M. (2014), “Causes of Waste across Multi-Tier Supply Networks: Cases in the UK Food Sector”, International Journal of Production Economics, Elsevier, Vol. 152, pp. 144–158.

Meredith, J. (1998), “Building Operations Management Theory through Case and Field Research”, Journal of Operations Management, Vol. 16 No. 4, pp. 441–454.

Narayanan, A., Sahin, F. and Robinson, E.P. (2019), “Demand and Order-Fulfillment Planning: The Impact of Point-of-Sale Data, Retailer Orders and Distribution Center Orders on Forecast Accuracy”, Journal of Operations Management, Vol. 65 No. 5, pp. 468–486.

Pramatari, K. and Miliotis, P. (2008), “The Impact of Collaborative Store Ordering on Shelf Availability”, Supply Chain Management: An International Journal, Vol. 13 No. 1, pp. 49–61.

Priyadarshi, R., Panigrahi, A., Routroy, S. and Garg, G.K. (2019), “Demand Forecasting at Retail Stage for Selected Vegetables: A Performance Analysis”, Journal of Modelling in Management, Vol. 14 No. 4, pp. 1042–1063.

Raman, A., DeHoratius, N. and Ton, Z. (2001), “Execution: The Missing Link in Retail Operations”, California Management Review, Vol. 43 No. 3, pp. 136–152.

Ramos, P., Santos, N. and Rebelo, R. (2015), “Performance of State Space and ARIMA Models for Consumer Retail Sales Forecasting”, Robotics and Computer-Integrated Manufacturing, Elsevier, Vol. 34, pp. 151–163.

Romsdal, A. (2014), Differentiated Production Planning and Control in Food Supply Chains.

Romsdal, A., Strandhagen, J.O. and Dreyer, H.C. (2014), “Can Differentiated Production Planning and Control enable both Responsiveness and Efficiency in Food Production ?”, Int. J. Food System Dynamics, No. April 2018, pp. 34–43.

Silver, E.A., Pyke, D.F. and Peterson, R. (1998), Inventory Management and Production Planning and Scheduling, John Wiley & Sons, Inc., Hoboken.

Småros, J., Lehtonen, J., Appelqvist, P. and Holmström, J. (2003), “The Impact of Increasing Demand Visibility on Production and Inventory Control Efficiency”, Journal of Physical Distribution & Logistics Management, Vol. 00 No. 4, pp. 336–354.

Spenhoff, P., Semini, M., Alfnes, E. and Strandhagen, J.O. (2014), “The Fit of Planning Methods for the Part Manufacturing Industry, a Case Study”, Advances in Manufacturing, Vol. 2 No. 2, pp. 165–172.

Ståhl Elvander, M., Sarpola, S. and Mattsson, S. (2007), “Framework for Characterizing the Design of VMI Systems”, International Journal of Physical Distribution & Logistics Management, Vol. 37 No. 10, pp. 782–798.

Steckel, J.H., Gupta, S. and Banerji, A. (2004), “Supply Chain Decision Making: Will Shorter Cycle Times and Shared Point-Of-Sale Information Necessarily Help?”, Management Science, Vol. 50 No. 4, pp. 458–464.

Wänström, C. and Jonsson, P. (2006), “The impact of Outsourcing on Materials Planning”, Journal of Manufacturing Technology Management, Vol. 17 No. 5, pp. 561–584.

Williams, B.D. and Waller, M.A. (2010), “Creating Order Forecasts: Point-of-Sale or Order History?”, Journal of Business Logistics, Vol. 31 No. 2, pp. 231–251.

Williams, B.D. and Waller, M.A. (2011), “Top-Down Versus Bottom-Up Demand Forecasts: The Value of Shared Point-of-Sale Data in the Retail Supply Chain”, Journal of Business Logistics, Vol. 32 No. 1, pp. 17–26.

Williams, B.D., Waller, M.A., Ahire, S. and Ferrier, G.D. (2014), “Predicting Retailer Orders with POS and Order Data: the Inventory Balance Effect”, European Journal of Operational Research, Elsevier B.V., Vol. 232 No. 3, pp. 593–600.

Yin, R.K. (2014), Case Study Research: Design and Methods, 5th ed., SAGE Publications Inc, California.

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